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A Scalable IoT-driven Smart Agriculture System: Ontology-based Inference and Automation for Hydroponic Farming

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Global warming and increasing disasters have worsened conditions for crop growth, intensifying the global food crisis alongside population growth. IoT technology is critical in smart agriculture, enabling the real-time monitoring and optimization of crop environments through big data analysis and machine learning. However, deep learning models struggle to adapt to diverse conditions owing to reliance on specific training scenarios. In this study, we propose an ontology-based smart agriculture system that emphasizes flexibility and scalability. Unlike deep learning models, ontology models can adapt to different crops or environmental changes by simply adding or modifying relevant classes, eliminating the need for extensive retraining. The system integrates IoT circuits for real-time data collection and ontology reasoning using Owlready2. It automates decision-making and device control, demonstrated in a hydroponic environment where it successfully responded to changes and executed appropriate actions. This approach combines enhanced adaptability, operational efficiency, and cost-effectiveness, lowering the barriers for farmers to adopt smart agriculture and enabling seamless management across diverse scenarios.

1. Introduction

With the increasing frequency of global warming and various natural disasters, the global environment is becoming less favorable for crop growth. At the same time, the world's population continues to rise, intensifying the food crisis. The United Nations estimates that by 2050, the global population will grow by an additional 2 billion, bringing the total from today's 7.8 billion to approximately 11 billion by the end of the century.(1) To enhance agricultural productivity, it is crucial to understand and predict how various environmental factors—such as soil conditions, fertilization, and irrigation—affect crop growth. By managing these environmental conditions effectively, we can significantly improve crop yields. IoT technology plays a vital role in monitoring the environments where crops are cultivated.

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In the context of Industry 4.0, IoT technology has been widely adopted in various fields, including healthcare, environmental monitoring, commerce, industry, and smart cities.[2] In recent years, information and communication technology has been integrated into traditional agricultural activities, paving the way for the Fourth Agricultural Revolution. Throughout history, agriculture has undergone four key revolutions: (1) the era of traditional agriculture, defined by human and animal labor; (2) the era of mechanized agriculture, characterized by the introduction of machines; (3) the era of automated agriculture, marked by rapid technological advancements; and (4) the current era of smart agriculture, driven by emerging technologies.[3]

In this era of smart agriculture, cutting-edge technologies such as wireless sensor networks,[4,5] IoTs,[6,7] agricultural robots,[8,9] drones,[10,11] artificial intelligence,[12,13] and cloud computing[14,15] are being applied to crop management. As these technologies are further developed and implemented, agricultural production is set to experience unprecedented revolutionary changes. These innovations not only enhance productivity but also optimize resource utilization, laying the foundation for precision agriculture. IoT technology, for instance, monitors environmental conditions on farmland in real time using various sensors that measure temperature, humidity, soil nutrients, and weather conditions. The data collected from these sensors are transmitted to a central system for analysis and processing. On the basis of the analysis, the system provides farmers or automated equipment with appropriate recommendations or instructions for actions such as irrigation, fertilization, and pest control.[16] IoT enables the automation and visual management of the entire agricultural production process, allowing each stage, from planting to harvesting, to be precisely controlled through data analysis.

The integration of artificial intelligence and machine learning algorithms makes decision-making in agriculture more scientific and efficient, enhancing both yield and quality. Moreover, the widespread use of agricultural robots and drones reduces reliance on manual labor while boosting production efficiency. Through the synergy of these technologies, not only can crop yields be increased, but resource consumption can also be significantly reduced, fostering sustainable agricultural development and effectively addressing the challenges posed by the global food crisis.

In this study, we focus on the development of smart agriculture, emphasizing the critical role of IoT in agricultural transformation, particularly through the application of sensor technology. We propose an IoT-based smart agriculture system specifically designed for hydroponic farming scenarios. It includes the development of an IoT data collection circuit capable of the real-time monitoring of key environmental parameters, such as pH, temperature, electrical conductivity, and water level. These data are transmitted to a cloud database via an integrated wireless fidelity (Wi-Fi) module for further analysis and management.

In addition, we integrated IoT with the proposed ontology model to enhance the system's flexibility and scalability. The ontology model allows for the addition or adjustment of relevant classes in response to changes in crop types or environmental conditions, eliminating the need for extensive model retraining or parameter adjustments. This enables the system to adapt more easily to diverse application scenarios and meet varying agricultural demands.

The findings demonstrate how precise data collection and analysis can significantly enhance the effectiveness of IoT-based agricultural practices. Furthermore, we provide an innovative approach to building flexible and scalable smart agriculture systems, laying a foundation for sustainable and efficient agricultural development.

2. Previous Research

With the ongoing development of IoT, the market has seen the emergence of low-cost sensors and open-source applications available for users to download. As a result, smart agriculture no longer requires significant financial investment, enabling farmers to adopt IoT technology in agriculture to achieve modern, data-driven farming. IoT-based agriculture leverages information technology to ensure that crops and soil receive the necessary resources for optimal health and productivity. The intelligent agriculture system is composed of three layers: the physical layer, the network layer, and the application layer, as illustrated in Fig. 1. Each layer performs distinct tasks while relying on data from others.[17,18]

Physical Layer: This layer comprises various sensors, terminal devices, agricultural machinery, wireless sensor networks, RFID tags, and readers. Common sensors include environmental sensors, animal and plant information sensors, and other agriculture-related sensors. These devices capture essential information such as temperature, humidity, wind speed, plant diseases, pests, and animal vital signs. The collected data are processed by embedded devices and transmitted to higher layers via the network layer for further analysis and decision-making.

Network Layer: The network layer serves as the infrastructure for IoT, encompassing a converged network formed by various communication networks and the Internet. Transmission can be achieved through wired technologies such as the CAN bus and RS485 bus, or wireless technologies such as Zigbee, Bluetooth, LoRa, and NB-IoT. The network layer not only transmits agriculture-related data collected by the physical layer to the application layer but also delivers control commands from the application layer to the physical layer, enabling devices to perform corresponding actions.

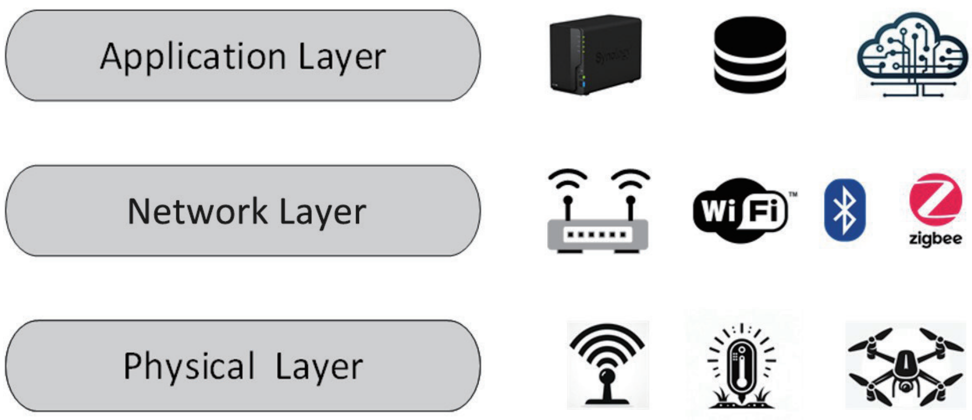


Fig. 1. (Color online) The three-layer architecture of the intelligent agriculture system consists of a physical layer, a network layer, and an application layer

Application Layer: The application layer is the highest level of the architecture and where the value of IoT becomes most evident. This layer includes intelligent platforms and systems used for the environmental monitoring and control of animals and plants, the early warning and management of pests and diseases, and the traceability of agricultural product safety. These applications help improve production efficiency, save time, and reduce costs. This architecture demonstrates how IoT technologies can revolutionize agricultural practices, bringing precision, efficiency, and sustainability to farming.

With the advancement of IoT technology, low-cost sensors and open-source applications have become available in the market.(19) This development allows farmers to implement IoT technology for modern agricultural management without the need for significant financial investment in smart agriculture. IoT-based agriculture leverages information technology to ensure that crops and soil receive the necessary conditions for optimal health and productivity.(20)

IoT agricultural research is categorized into three types of application based on the level of intelligence: monitoring, monitoring with basic analysis, and intelligent applications. The role of monitoring-only IoT systems in smart agriculture lies at the core of the “data supply chain.” These systems provide real-time, reliable data to support the analysis and decision-making processes required by more advanced smart applications. While these systems do not possess intelligent functions themselves, they serve as a critical foundation for higher-level intelligent processing and automation. For instance, Mahaidayu *et al.* proposed the use of IoT to monitor pH and conductivity parameters in real time for hydroponic farming.(21) Hidayanti *et al.* developed a system that combines IoT technology and solar power to remotely monitor and maintain various parameters of hydroponic solutions.(22) Similarly, Sung *et al.* implemented a water quality monitoring system utilizing sensors for turbidity, temperature, pH, conductivity, and total dissolved solids.(23) Although IoT systems with monitoring functions provide essential data support for smart agriculture applications, they lack advanced data processing and real-time decision-making capabilities. As a result, they are not equipped to respond flexibly to dynamic demands and large volumes of data. These systems play a primary role in supplying data but must work in tandem with intelligent systems to achieve fully automated, smart agricultural outcomes.

IoT systems with both data collection and control capabilities play a more critical role in smart applications than agricultural IoT systems that are limited to monitoring functions. These advanced systems not only collect real-time environmental and equipment data but also automate control processes. For example, Mohammed *et al.* utilized IoT solutions to manage modern underground irrigation systems, improving irrigation management for date palms in arid regions.(24) Similarly, Hsu *et al.* developed a smart farm irrigation system that uses IoT technology for remote monitoring.(25)

However, such systems still face significant limitations owing to the lack of intelligent analysis. This results in low data utilization efficiency, limited decision support, insufficient resource optimization, and a lack of predictive maintenance and early warning capabilities. These systems cannot be fully managed intelligently, as they still rely on manual data analysis and decision-making, which constrains the potential benefits of smart agriculture. To overcome these shortcomings, agricultural IoT systems need to incorporate technologies such as big data analysis and machine learning to achieve higher levels of intelligent management and decision support. In recent years, many researchers have focused on integrating big data analysis, machine learning, and other technologies into smart agriculture. For example, Bu and Wang proposed an IoT-based smart agricultural system that leverages edge cloud computing, combining advanced information technologies such as AI and cloud computing with agricultural production to boost food yields.(26) This system integrates AI models with deep reinforcement learning in the cloud, allowing for real-time, intelligent decision-making, such as determining the optimal amount of water for irrigation to enhance crop growth environments. Sharma *et al.*(13) applied image-based analysis for crop prediction, using images taken in the field under different lighting conditions to assess the nitrogen status of wheat crops and prevent overfertilization. They also used artificial neural networks to effectively identify wheat crops alongside unwanted plants and weeds. However, deep learning models are typically optimized for specific tasks or data, meaning they perform best in scenarios or tasks that closely resemble their training data. While these models offer accuracy within a limited scope, they remain constrained when applied to vastly different farms or crop types.

To address this issue, we propose a smart agriculture system based on an ontological model. Unlike deep learning models, which are task-specific, the ontological model offers greater versatility owing to its flexible and scalable knowledge representation. Through a well-defined semantic structure, the ontological model does not depend on specific data or tasks, allowing it to be extended and applied to a variety of scenarios. This flexibility gives the ontological model superior adaptability in intelligent applications, the semantic web, and multi-domain knowledge management.

3. Research Architecture

Owing to the controllability of the environment, high-precision data collection, high experimental repeatability, and the convenience of technical validation, an indoor hydroponic environment was selected as the testing scenario for the intelligent agriculture system. This environment utilizes sensors, solenoid valves, hydroponic containers, and other equipment for simulation. The system's architecture is divided into three layers: the physical layer, the network layer, and the application layer, as illustrated in Fig. 2.

The specific functions of each layer are as follows:

Physical Layer: The physical layer includes various environmental monitoring sensors, such as pH sensors, temperature sensors, and water level sensors, in addition to solenoid valves for control.

Network Layer: The network layer is responsible for transmitting the data collected from the physical layer, as well as the control commands generated by the application layer. It serves as a bridge between the physical world and the digital environment.

Application Layer: The application layer consists of cloud-based applications, such as databases for storing data transmitted from the network. The data from the physical layer is stored and monitored in the database, with data visualization tools provided for easy observation by users. In certain scenarios, the application layer extracts data from the database to perform analysis and generate control commands, which are sent back to the devices for execution.

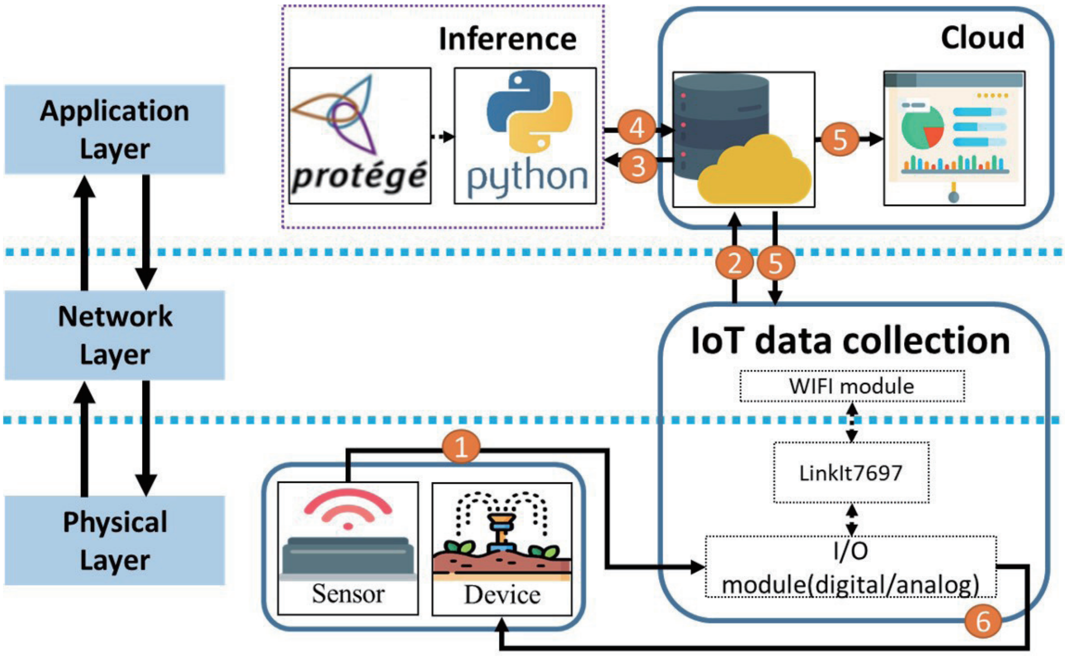


Fig. 2. (Color online) Ontology-based smart agriculture system architecture diagram.

This multilayer structure allows for efficient environmental monitoring and automated control within the hydroponic system.

Figure 2 illustrates the detailed operational process of the intelligent agriculture system architecture.

1. The IoT data collection circuit gathers data from sensors via I/O points.
2. The Wi-Fi module within the IoT data collection circuit uploads the sensor data to the cloud database for storage.
3. Data is extracted from the database and analyzed using a hydroponic ontological model built with the Owlready2 suite.
4. The inference results are stored back into the database.
5. The IoT collection circuit retrieves these inferences and visualizes both the collected sensor data and the status of devices (e.g., solenoid valves).
6. Finally, the inference results are used to control devices such as solenoid valves via the I/O points of the IoT data collection circuit.

This system enables the automated, data-driven control of the hydroponic environment for precision agriculture.

4. Methods

The objective of this study is to design and implement a smart agricultural IoT system for data collection, storage, inference, and control to ensure that crops are maintained in an optimal environment. The following outlines the specific methods and steps involved in constructing the system:

4.1 Physical Layer

The physical layer is a fundamental part of the IoT architecture, responsible for interacting with the physical world and converting real-world data into processable information. This layer consists of sensors, actuators, and embedded devices, allowing IoT systems to collect and respond to environmental information in real time. In this study, a hydroponic environment was used for validation. The solenoid valve is used as the actuator in this system, controlling water levels and nutrient distribution. Aside from the actuator, the following sensors were selected for monitoring in the physical layer:

pH Sensor: pH measurement is critical in hydroponics, as it affects nutrient uptake, root health, microbial balance, and system stability. By accurately monitoring pH levels, hydroponic systems can optimize plant growth, improve productivity, and integrate automated management using IoT technology.

Temperature Sensor: Temperature monitoring plays a crucial role in plant growth, nutrient absorption, dissolved oxygen levels, microbial activity, and disease risk. Accurate temperature control ensures optimal conditions for healthy plant development, improving both crop quality and yield.

Electrical Conductivity Sensor: Conductivity measurement provides essential information about nutrient concentration and water quality. Monitoring electrical conductivity (EC) allows growers to adjust nutrient levels, maintain balance, and optimize plant growth and yield.

Water Level Sensor: Monitoring water levels is critical for root health, uniform nutrient distribution, and stable system operation. Proper water level management prevents oxygen deprivation or nutrient deficiencies and improves resource efficiency.

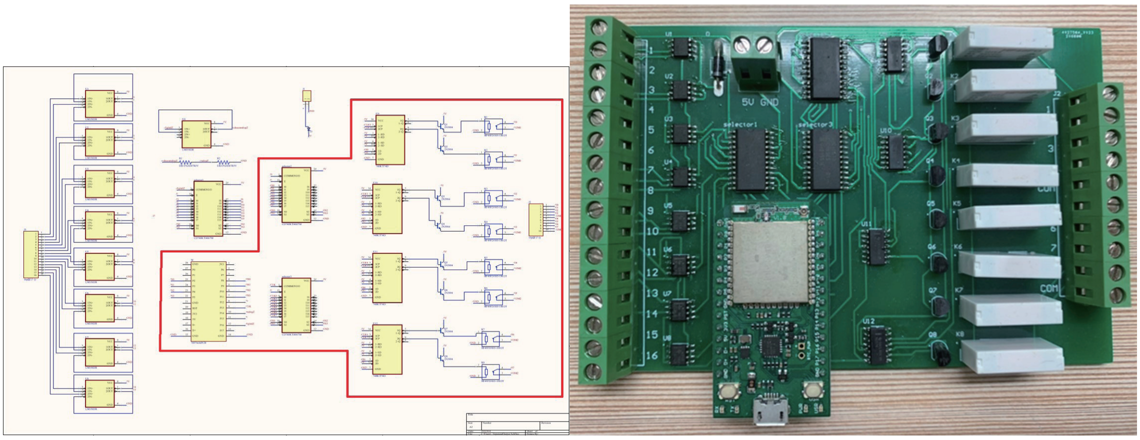
The microcontroller units (MCUs) in the physical layer are responsible for data collection, device control, communication management, and energy efficiency optimization. They play a key role in the intelligent and automated operation of IoT devices. The LinkIt 7697 IoT development board was chosen for this study owing to its built-in Wi-Fi, Bluetooth capabilities, low-power design, and rich I/O ports. Since the sensor and actuator signals do not directly match the I/O ports of the LinkIt 7697, a peripheral circuit was designed to interface them, as shown in Fig. 3.

4.2 Network Layer

The LinkIt 7697's built-in Wi-Fi module is utilized as the network layer of the IoT system, offering efficient, secure, and low-power wireless data transmission. It supports a broad range of connectivity options and flexible integration, making it ideal for IoT applications, including smart agriculture and smart cities.

4.3 Application Layer

The application layer includes the cloud-based MySQL database and the ontological model. As shown in Fig. 4, the cloud server Network Attached Storage serves as the database platform,



(a) (b)

Fig. 3. (Color online) IoT data collection circuit: (a) layout diagram and (b) physical printed circuit board.

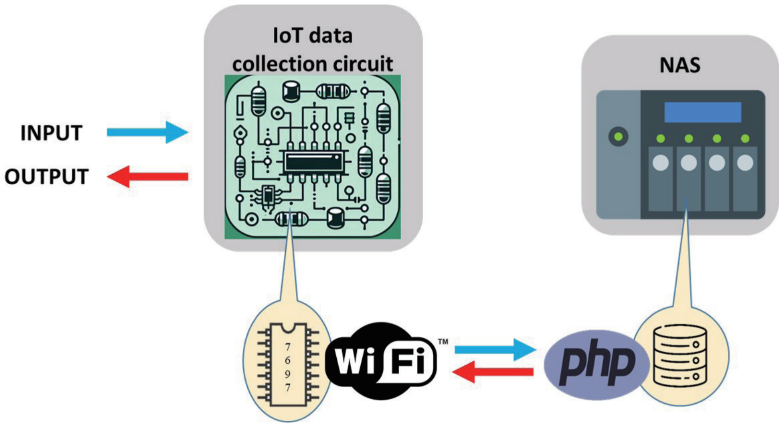


Fig. 4. (Color online) Information operation flow diagram of the IoT data collection circuit and cloud database.

offering scalability, easy data backup, and low cost. Data management is performed using phpMyAdmin, a web-based MySQL management tool. The LinkIt 7697 of the physical layer retrieves data from sensors and stores it in the database using SQL syntax through PHP, while control commands are similarly processed and executed via the IoT data collection circuit.

The following paragraph will explain the process of building the ontological model. The ontological model in this study is constructed using Protégé, a tool that establishes knowledge ontologies to represent and describe knowledge using Classes, Individuals, and Properties. This model allows for better knowledge representation and inference in the hydroponic system. In Table 1, the source of knowledge for this ontological model is derived from the Technical Manual for the Production and Management of Vegetable Crops (2022), published by Taiwan's Agriculture and Food Agency, Ministry of Agriculture.(27)

In ontology, Class, Individual, and Property are three fundamental concepts that are closely related to each other. In ontology, Class defines the type of object, Individual is the concrete

Table 1
Basic formula of vegetable hydroponic liquid.

Vegetable groups	EC (mS/cm)		pH	
	spring/summer	autumn/winter	spring/summer	autumn/winter
A group: Chinese cabbage, amaranth, rapeseed, water spinach	1.02–1.28	1.28–1.70	5.5–6.0	6.0–6.5
B group: Crown daisy, Japanese crown daisy, mustard greens	1.28–2.13	1.70–2.55	5.5–6.0	6.0–6.5

instance of that type, and Property describes the characteristics of these instances. The relationship among these three forms the fundamental structure of ontology, allowing us to organize and understand various aspects of knowledge. Below are the explanations among these three.

Class is an abstract concept used to define a group of objects that share common characteristics or properties. It is a conceptual collection that describes the common features of a certain category of entities. For example, "Human" can be a Class that encompasses the characteristics of all humans. In this study, Class is created to represent the entities in the system. For example, the class Pump includes different control entities such as the pH, EC, and water level control pumps. Vegetable types, such as Vegetables A and B, are categorized under the class Vegetable (as shown in Fig. 5).

Individual refers to a concrete entity that is a specific realization of a Class. Each Individual is a member of a Class and possesses the properties defined by that Class. Individual in this study is then created under the established classes. Each pump (e.g., pH and EC control pumps) and vegetable type (e.g., Vegetables A and B) is defined as an individual within their respective class (as shown in Fig. 6).

Property is a specific entity used to describe the characteristics or attributes of a Class or Individual. It can be viewed as the qualities or features of a Class or Individual. Property in this study is added to define the specific characteristics of individuals. For instance, a property could describe the state of a pump, whether it is active or inactive (as shown in Fig. 7).

Next, rules are established on the basis of the basic formula of hydroponic nutrient solutions shown in Table 1, and these are categorized into two types of vegetables: A and B. We retrieve data from the database to store the properties that change the state of the individual based on sensor values. This information is used to infer whether to open the solenoid valve to increase the hydroponic nutrient solution or regular water level. Since temperatures vary across regions in spring and summer compared with autumn and winter, a temperature of 20 °C is used as the cutoff point to determine whether it is spring/summer or autumn/winter (as shown in Fig. 8). Inference rules are established to trigger control actions. For example, when pH falls below a specified threshold, the system infers that the pH pump needs to activate to add more nutrient solution. After generating inferences, the results are uploaded to the cloud database for storage, where they can be used for controlling devices, such as opening solenoid valves to adjust the hydroponic environment automatically. This process allows the ontological model to represent a flexible and extensible knowledge structure, enabling smart inferences for the hydroponic system.

```
class pump(Thing):
    pass
  class vegetable(Thing):
    pass

  class possible_for_PHpump_open(Thing):
    pass
  class possible_for_PHpump_close(Thing):
    pass
  class possible_for_ECpump_open(Thing):
    pass
  class possible_for_ECpump_close(Thing):
    pass
  class possible_for_waterlevelpump_open(Thing):
    pass
  class possible_for_waterlevelpump_close(Thing):
    pass
  class possible_for_vegetable_kind(Thing):
    pass
```

Fig. 5. Category diagram of the ontological model of hydroponic vegetables established by Owlready2.

```
PHpump = pump("PHpump")
ECpump = pump("ECpump")
waterlevelpump = pump("waterlevelpump")
A = vegetable("A")
B = vegetable("B")
```

Fig. 6. Individual diagram of the ontological model of hydroponic vegetables established by Owlready2.

5. Results and Discussion

The data collected in this study include pH, EC, temperature, and water level. The units that need to be controlled are the pH, EC, and water solenoid valves, which are used to adjust the nutrient solution or water level. First, environmental data are captured via the IoT and uploaded to a database for storage. The crop type used in this study is vegetable type A, as illustrated in Fig. 9(a). As time progresses, plants gradually consume water and nutrients, resulting in decreases in pH, EC, and water level, as shown in Fig. 9(b).

The inferred control commands for the pH, EC, and water solenoid valves are also stored in the database, as depicted in Fig. 10. A, B, and C represent the pH, EC, and water solenoid valves, respectively, with their current control statuses being ON/OFF/ON.

Once the pH, EC, and water level are uploaded to the database, a Python program retrieves the data and makes inferences based on pre-established rules within the hydroponic ontology model. The inference results are shown in Fig. 11, indicating that the pH concentration is sufficient, so the pH solenoid valve should be closed. Moreover, the EC solenoid valve should be opened owing to insufficient EC, and the water solenoid valve remains open to replenish the

```
class PHpump_on(DataProperty):
     range  = [bool]
  class PHvalue_high(DataProperty):
     range  = [bool]
  class PHvalue_low(DataProperty):
     range  = [bool]
  class ECpump_on(DataProperty):
     range  = [bool]
  class ECvalue_high(DataProperty):
     range  = [bool]
  class ECvalue_low(DataProperty):
     range  = [bool]
  class waterlevelpump_on(DataProperty):
     range  = [bool]
  class waterlevelvalue_high(DataProperty):
     range  = [bool]
  class waterlevelvalue_low(DataProperty):
     range  = [bool]
  class vegetable_A(DataProperty):
     range  = [bool]
  class vegetable_B(DataProperty):
     range  = [bool]
```

Fig. 7. Attribute diagram of the ontological model of hydroponic vegetables established by Owlready2.

water supply. These inference results are then stored back in the database and sent to the IoT device, which controls the solenoid valves accordingly. As a result, the EC and water level are adjusted and increased through the control commands issued to the solenoid valves, as demonstrated in Fig. 12.

While general MCUs can be used to capture sensor data and control devices, they are limited to simple input–output conversions. As environmental complexity increases, the control logic becomes exponentially more complicated, and MCUs, with their limited memory, cannot handle large amounts of data. In this study, the database serves as a central hub for recording and querying data, while the custom ontological description environment ensures a shared data foundation for collaboration. The ontology model processes this data to make inferences and then applies these results to the control system.

One of the key advantages of using an ontology model is its scalability. When new equipment is added or removed, only the relevant categories within the model need to be updated, leaving the existing framework and functionality unaffected. For example, if Vegetables A and B are rotated, only two vegetable types need to be classified within the model. If a third vegetable, type C, is introduced, an additional category can be easily added without affecting the previous settings. This flexibility and independence make ontology-based systems more adaptable and scalable than other intelligent systems.

Deep neural networks,(28) support vector machines,(29) random forest regression,(30) k-nearest neighbors algorithm,(31) and deep learning(32) exemplify the diverse and highly effective

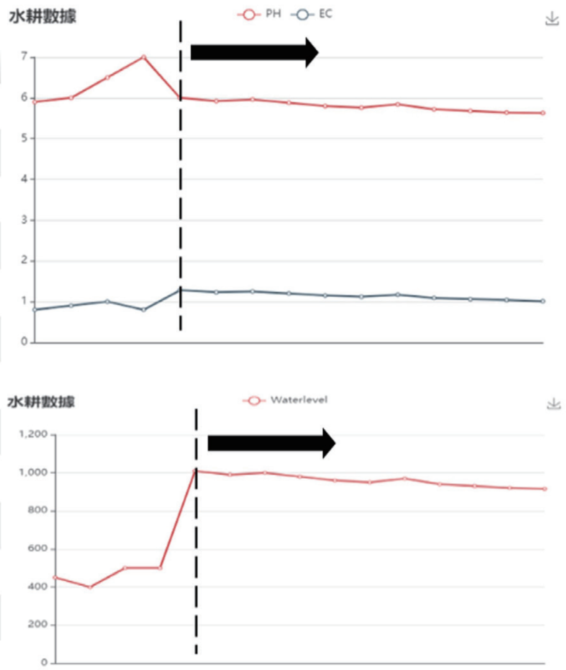
```
if mysqlKind =='A':#蔬菜種類A
    if mysqlTemperaturevalue >20:  #A春夏
        if mysqlPHvalue > 6 :
            PHpump.PHvalue_high = [True]
            PHpump.PHvalue_low = [False]
        elif mysqlPHvalue < 5.5:
            PHpump.PHvalue_high = [False]
            PHpump.PHvalue_low = [True]
        else:
            PHpump.PHvalue_high = [False]
            PHpump.PHvalue_low = [False]
        if mysqlPHpumpStatus == 1:
            PHpump.PHpump_on = [True]
        else:
            PHpump.PHpump_on = [False]

        if mysqlECvalue > 1.28 :
            ECpump.ECvalue_high = [True]
            ECpump.ECvalue_low = [False]
        elif mysqlECvalue < 1.02 :
            ECpump.ECvalue_high = [False]
            ECpump.ECvalue_low = [True]
        else:
            ECpump.ECvalue_high = [False]
            ECpump.ECvalue_low = [False]
        if mysqlECpumpStatus == 1:
            ECpump.ECpump_on = [True]
        else:
            ECpump.ECpump_on = [False]
```

Fig. 8. Rule diagram of the ontological model of hydroponic vegetables based on Owlready2.

applications of AI in hydroponic agriculture. The application of AI in hydroponic agriculture introduces transformative advantages in precision control and intelligent management, significantly enhancing the operational efficiency and accuracy of hydroponic systems. AI technologies enable real-time parameter adjustments, effectively reducing the waste of water and fertilizers. Their data-driven nature empowers systems with robust decision-making capabilities, leveraging the analysis of extensive environmental datasets to optimize cultivation conditions. Furthermore, AI facilitates improved crop health management, allowing for the early detection of diseases and rapid responses, thereby considerably advancing the sustainability and productivity of agriculture. These characteristics position AI not only as a pivotal driver of hydroponic agriculture but also as a cornerstone for the future development of smart agriculture.

Nevertheless, AI-based models exhibit inherent limitations. They primarily operate within localized learning domains and model existing data with high precision but struggle to extrapolate to scenarios beyond the known parameter ranges.[33] By contrast, ontology-based intelligent agricultural systems overcome these limitations. Ontology, as a flexible and scalable knowledge representation approach, organizes and describes knowledge through the structure of

PH	EC	Waterlevel	Temperature
5.63	1.01	915	25
5.64	1.04	920	25
5.68	1.06	930	25
5.72	1.09	940	25
5.84	1.17	970	25
5.76	1.12	950	25
5.8	1.15	960	25
5.88	1.2	980	25
5.96	1.25	1000	25
5.92	1.23	990	25
6	1.28	1010	25
7	0.8	500	25



(a) (b)

Fig. 9. (Color online) (a) pH, EC, temperature, and water level of hydroponic nutrient solution stored in cloud database. (b) Graphs of pH, EC, and water level of hydroponic nutrient solution over time.

←T→	dtime	A	B	C
編輯 複製 刪除	5	1	0	1

A	B	C
ON	OFF	ON

Fig. 10. (Color online) Control commands of the solenoid valve stored in the cloud database.

```
possible_for_PHpump_open: []
possible_for_PHpump_close: [test5.PHpump]
possible_for_ECpump_open: [test5.ECpump]
possible_for_ECpump_close: []
possible_for_waterlevelpump_open: [test5.waterlevelpump]
possible_for_waterlevelpump_close: []
possible_for_vegetable_kind: [test5.A]
* Owlready2 * Pellet took 1.6613082885742188 seconds
* Owlready * (NB: only changes on entities loaded in Python
are shown, other changes are done but not listed)
```

Fig. 11. (Color online) Inferred results based on the current status of hydroponic systems.

classes, individuals, and properties. Its core advantage lies in its high scalability; when environmental conditions or task requirements change, only the relevant classes need to be added or adjusted without requiring model retraining or parameter tuning. For instance, integrating a new vegetable type into the system merely involves adding a corresponding class

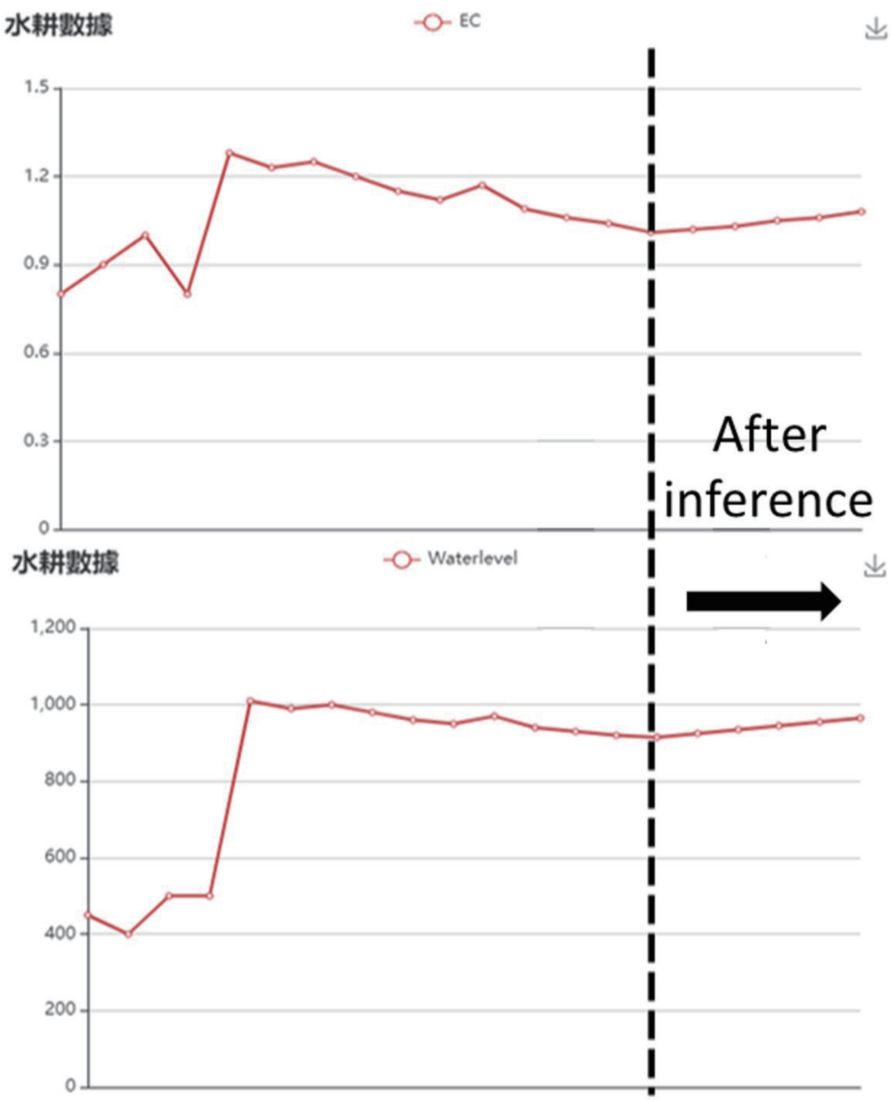


Fig. 12. (Color online) EC and water level records before and after the ontological model inference.

or instance, a process that is both efficient and nondisruptive to the existing framework and functionality.

Historically, numerous scholars have explored the application of ontologies in agriculture. For example, Aminu *et al.*(34) focused on knowledge management for maize crops, whereas Abbasi *et al.*(35) developed an ontology model for aquaculture and hydroponic systems in vertical farming. Alharbi *et al.*(36) proposed an ontology model for managing plant diseases and pests. However, these studies primarily concentrated on the theoretical aspects of ontology modeling and semantic reasoning, rather than its practical implementation with IoT technologies.

In contrast, the contribution of this study lies in the development of a scalable intelligent agricultural system based on IoT technologies, integrating ontology modeling with hardware control. This system not only offers semantic reasoning capabilities for knowledge management but is also successfully applied to hydroponic agricultural scenarios, enabling the real-time monitoring, inference, and automated control of environmental data. Compared with previous studies focusing on knowledge representation, the experimental results of this study demonstrate the system's precise regulation of pH, EC, and water level in the hydroponic environment, effectively transforming semantic reasoning outputs into actionable physical behaviors.

6. Conclusion

With advancements in science and technology, IoT is gradually being introduced into agriculture to modernize traditional farming practices. This shift aims to boost productivity while reducing the need for manual labor, thus moving towards smart agriculture. A key factor in achieving this transformation is establishing a seamless connection between the physical world and the cyberspace. However, coordinating and optimizing the interaction between these two domains, especially given the large number of sensors and devices involved, present a significant challenge.

In this study, we designed an IoT data collection circuit to address the connectivity issue between the real world and the cyberspace, enabling real-time data transmission to the network. The collected data are directly uploaded to a database for storage, which eliminates the inefficiencies caused by different transmission protocols and data types, ensuring that the data can be effectively utilized for future applications.

The use of ontology in our system provides significant scalability, allowing for flexible adaptation to changes in scenarios or tasks. New categories can be easily added to the model without disrupting existing services and functionalities. Furthermore, the low cost of the hardware and software used makes it more accessible for farmers, lowering the entry barrier for adopting smart agriculture solutions.

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