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Integration of IoT and biotechnology for real-time crop monitoring and management in smart agriculture

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Abstract

Objective

Modern problems including rising food demand, limited resources, and environmental degradation can be effectively addressed through the revolutionary practice of smart agriculture (SA). Meeting global demand while reducing environmental effect is a challenge for traditional farming practices. By enhancing agricultural methods, increasing crop yields, and decreasing resource consumption, the combination of Biotechnology (BT) with SA provides a revolutionary solution.

Material and methods

Smart Agriculture systems' incorporation of data analytics and Deep Neural Networks (DNN) has increased the optimization potential of agriculture even further. In order to improve crop management, decrease waste, and increase overall farm production, farmers can use data-informed decisions made possible by DNN algorithms to get practical insights into crop health, growth trends, and ideal farming practices.

Results

A Real-Time Crop Monitoring and Management (R-CMM) system integrating DNN, Internet of Things (IoT), and Biotechnology (BT) is proposed in this research as an application of Smart Agriculture. By collecting biological signals from the environment using tiny, renewable, and non-invasive sensors, IoBT provides real-time data on plant health, soil conditions, and climate

parameters. With this, automated administration of crop systems and continuous monitoring from a distance are both made possible, cutting down on personnel expenses and increasing overall efficiency.

Conclusions
Indoor crop plantation management relies on a number of critical characteristics, including temperature, humidity, soil moisture, and light intensity, all of which the R-CMM system uses to keep checks on. The platform's use of DNN algorithms allows for more effective and accurate farming by predicting when crops may experience stress, optimizing the allocation of resources, and detecting early indications of disease or pest infestations.

Keywords: Biotechnology, deep neural networks, internet of bio things, sensors, smart agriculture

Paper Type: Research Paper.

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Introduction

One of the most important issues of contemporary life is how to feed a population that is expanding every day sustainably. To feed around 1.8 billion people by 2055, the nation's farming and food manufacturing sector will face significant challenges due to a lack of arable land, water, and electrical sources (Pingali et al. 2019). Several significant issues have emerged in agricultural growth and development, including declining and fragmented land ownership, global climate change, depletion and degradation of natural resources, stagnant farm incomes, lack of an eco-regional approach, agricultural trade liberalization, and limited employment opportunities in the non-farm sector. Adopting newly developed technologies is thus acknowledged as a critical strategy to improve agricultural productivity in the future (Karunathilake et al. 2023).

Precision agriculture facilitates various agricultural practices such as comprehending the characteristics of the soil in a particular area, improving soil quality, choosing suitable crops, managing irrigation, planning planting and harvesting schedules, administering disease treatments, managing pests and weeds, applying nutrients, monitoring the crops, and predicting yields (Veerasamy & Fredrik 2023). Precision agriculture, when paired with highly accurate tools for decision-making and early warning systems, offers an improved understanding of the spatial needs of a particular agricultural area (Angin et al. 2020). These technologies help to eliminate excessive operations and give timely information for effective management (Sanjeevi et al. 2020). SA makes the agricultural sector less vulnerable to climate change by using water, chemicals, and energy best (Zoran et al. 2022). This is especially important during droughts, extreme weather events, and the spread of pests and diseases caused by changing climates (Azadi et al. 2021). When connected to the field equipment, CMM systems can be used to figure out how much fertilizer to use, the best time to spray, and the exact amount and timing of irrigation (Camgözlü & Kutlu 2023). Farmers can easily manage important tasks from afar with this technology, which saves them time, energy, and resources. In addition to increasing output, this may also teach people how to make accurate predictions, which can help them make good decisions at the right time (Radhika & Masood 2022). Real-time predictions and environmental parts based on data give farmers more options for preparing their crops for bad weather (Ulibarri et al. 2022; Vranić & Glišović 2018).

It is becoming increasingly important for farmers to have technology to keep up with this growing need. Some examples of how SA technology is becoming more popular are improvements in seed breeding and the ability to use sensors and IoT features for R-CMM (Shaikh et al. 2022; Lopes 2023). Farmers can use local information along with past and present weather data, crop performance histories, and other things to help with CMM. One agricultural innovation that is expected to grow at a CAGR (compound annual growth rate) of 6.69% from 2020 to 2024 is BT. In 2019, about $95 billion was spent in this area (Surendar et al. 2024). Some BT innovations are methods and tools for improving organisms by changing their size, color, or productivity through seed reproduction (Rose & Chilvers 2018; Bronson 2019).

SA and plant BT are complementary fields that have the potential to improve agricultural productivity, ecological responsibility, and excellence. Plant BT is modifying a crop's genes and traits to increase the crop's value, resistance, or effectiveness (Radhika & Masood 2022). SA uses sensors, analytics, and automation to improve R-CMM while reducing resource use and environmental impact (Mumtaj Begum 2022). Combining these two fields of study might result in more effective and efficient agriculture solutions. Moreover, data generation in agriculture and biotechnology has greatly increased in recent years due to the very rapid development of high-performance technologies (Mohammadabadi et al. 2024). These data are obtained from studying products, foods, and biological molecules to understand the role of different aspects of agriculture in determining the structure, function, and dynamics of living systems (Hamidi et al. 2017). Artificial neural networks have been proposed to alleviate limitation of traditional methods and can be used to handle nonlinear and complex data, even when the data is imprecise and noisy (Hamidi et al. 2017). Agricultural data can be too large and complex to handle through visual analysis or statistical correlations. This has encouraged the use of machine intelligence or artificial intelligence (Ghotbaldini et al. 2019). Thus, the main goal of this study was to biosensor application.

Materials and methods

Integrating IoT and BT for R-CMM in SA: An R-CMM framework's primary objective is to offer an extensive structure encompassing all essential tasks for conducting independent bio-sensor gathering, regional archiving, and isolated communication. The information is acquired through a network of sensors and sent to a gateway, which is then exchanged with the user over the cloud. Hence, the framework for SA with IoT bio-sensors (Figure 1) offers an internet-based User Interface (UI) that enables users to remotely sign in, view, and evaluate past information for either an individual sensor or an entire site. The sensor information consists of discrete components, each with a unique ID and assigned to an individual location. Every gadget independently gathers data from the surroundings using probes and transmits it to the base station (BS) using a wireless network such as WiFi, ZigBee, or LoRa technology. Every node in an internet connection may function as either a basic server or, in the case of a distributed network, as both an end user and an additional node simultaneously, subject to its networking topology (Radhika & Masood 2022).

An advantage of the architecture is that every sensor operates autonomously, enabling seamless extensions and plug-out activities without requiring reconfiguration of the remaining sensors. The information acquired from gadgets is transmitted to a BS, which serves as a gateway and transfers the information to the cloud via an immediate internet link. Due to the ability to track several sites within an identical region, it is possible to deploy many BS at various places. To prevent the need for numerous robust internet connections for every gateway, a solution is to use a handheld device, like an airborne drone, which may regularly gather information from every BS. This data can then be sent to one controller unit, which will then be uploaded to the web-based system. Using an SA structure makes it feasible to organize several devices and harmonize the duties to be executed. This includes determining the frequency at which the unmanned aircraft should take off to gather information from every BS and establishing the paths to be followed (Radhika & Masood 2022).

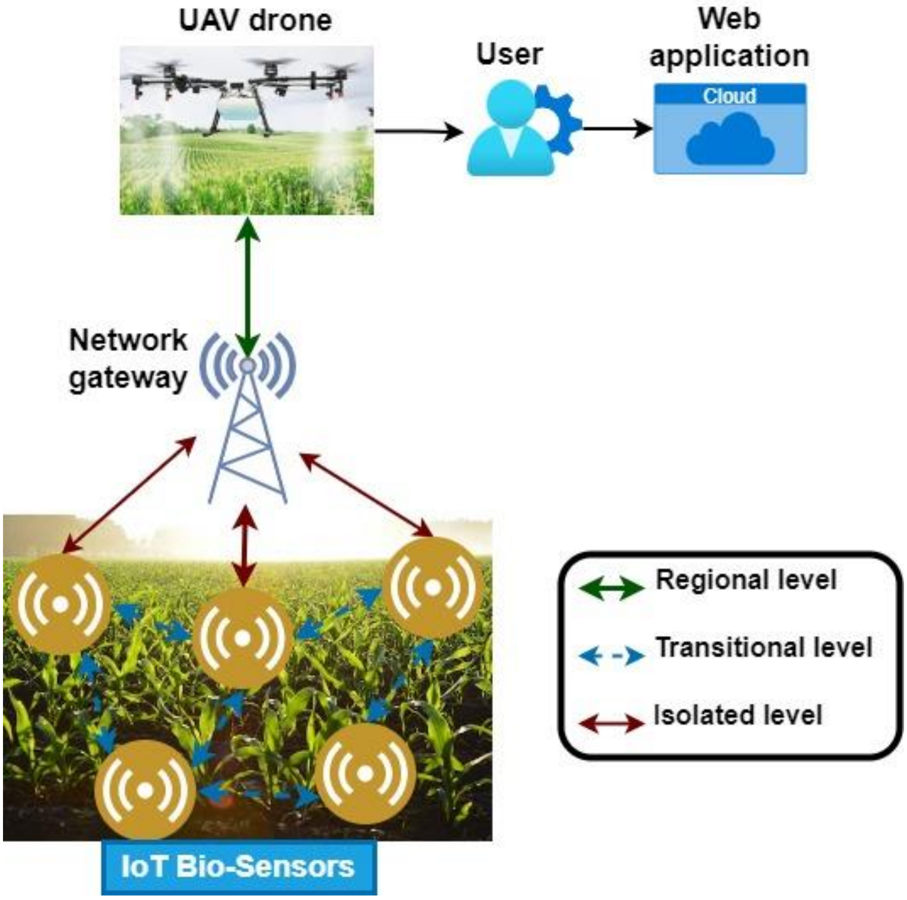

Figure 1. General framework for SA with IoT bio-sensors

The combination of IoT and BT approaches, and the precision of IoBT communication can successfully address the challenges associated with the rapid and exact assessment of crop well-being. Combining the IoBT with SA offers a thorough R-CMM framework implementation method. Integrating DNN algorithms with the IoBT enables the creation of intelligent devices capable of delivering timely, accurate, and data-driven evaluations about the health and condition of plants (Radhika & Masood 2022). This revolutionary union helps us learn more about crop diseases and gives us a way to prevent them and treat specific ones. As a result, it makes possible the start of a new era in agriculture called SA, which has the potential to boost productivity and sustainability greatly.

Cloud-IoBT is a new service that makes it easier to install sensors in remote areas. It's a free web-based solution. This solution makes operation and integration go smoothly. Farming has become easier to do thanks to advances in technology. Farmers have adopted new methods that have greatly increased agricultural productivity. The IoBTs are groups of sensors, robots, cell phones, and drones that work together or with little help from people. These gadgets do different things and collect data while working together, which makes things faster and more accurate. In the field of SA, AI technologies are used to check and study the environmental conditions of farmland efficiently and choose the best crops and R-CMM techniques to grow. Many things are considered in these evaluations, like the soil type, weather forecasts, and water availability (Karunathilake et al. 2023).

Figure 2 shows the integration of IoT and BT for R-CMM in SA using DNN. Integrating vast amounts of data from many sources will provide significant benefits in agriculture via IoBT technology. The temperature and nutritive data of a farm of significant size are sent to a centralized BS. The data from several bio-sensors does not justify the expense and complexity involved with the IoBT. If nodes are aggregated in clusters of ideal size, the potential bandwidth may be comparable to that of the IoBT. Unmanned aerial vehicles (UAVs) equipped with bio-sensors and multispectral imaging cameras are used to collect data as they fly over agricultural areas. Afterward, devices use this data to execute DNN algorithms and assess and detect problems that impact R-CMM **(**Camgözlü & Kutlu Y 2023).

DNN: The DNN architecture enables the categorization of both normal and compromised data packets **(**Camgözlü & Kutlu Y 2023). DNN is a kind of neural network similar to a conventional Neural Network (NN). The key difference is that DNNs include many hidden layers between the input and output layers. The DNN architecture has two separate phases: training and testing. This supervised learning technique is very effective when a larger dataset is used for training. The input values are multiplied by their corresponding weights in the hidden layer and added to the neuron's bias. The formal expression of this process is denoted by Equation 1:

$$C_{h(x)} = (\sum_{m=1}^{M} w_{xm} F_{I_j}) + b_x \quad (1)$$

The variable b_x represents the bias, which is a fixed value. The value of x is incremented by 1, 2, and subsequent numbers. Let K represent the quantity of input and hidden nodes. The link weight between the input and hidden layer is denoted as w_{xm}. The variables M and K denote the input and hidden neurons in the first hidden layer, respectively. The symbol F_{I_j} denotes the selected set of optimal features generated via the use of IoBT. The set is used as the input for the DNN algorithm, with m being a number ranging from 1 and M.

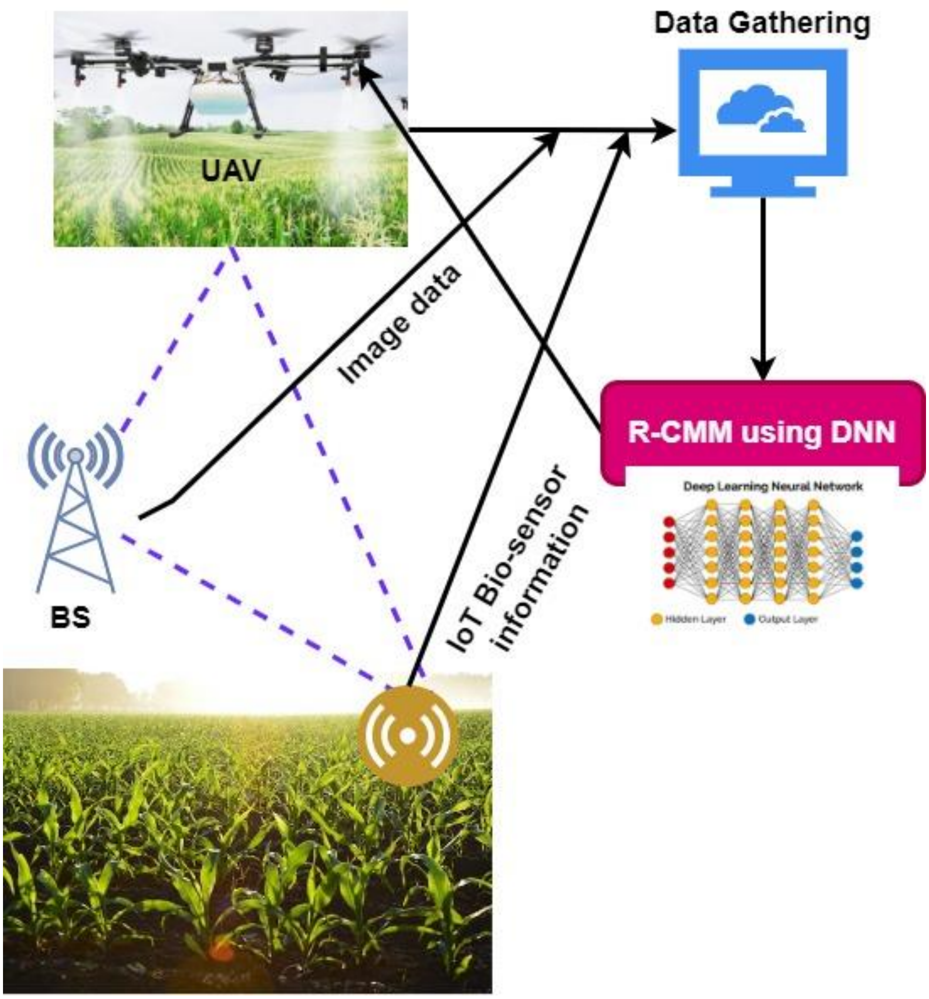

Figure 2. Integration of IoT and BT for R-CMM in SA using DNN (Camgözlü & Kutlu Y 2023)

The term $C_{h(x)}$ denotes the result produced by the hidden layer of the whole network. The result of the hidden layer is dictated by the activation function, as specified in Equation 2:

$$A\left(C_{h(x)}\right) = \frac{1}{1+e^{-C_{h(x)}}} \qquad (2)$$

The sigmoid activation value is represented by the symbol " $A(.)$". Equation 3 represents the mathematical computation performed at the output layer. It involves multiplying the output of the hidden layer by the weights that link the hidden and output layers. Subsequently, this product is included in the bias function b_x.

$$C_{O(x)} = A\left(\sum_{n=1}^{N} w_{xn} A\left(C_{h(x)}\right)\right) + b_x \qquad (3)$$

The variable w_{xn} represents the weight that connects the concealed and output layers. The output layer's activation function is the complete network's final output.

As DNNs and IoBT come together, they change how R-CMM is done in SA. IoBT devices collect a lot of data, like biosensors built into plants and soil, and this method uses advanced DL models to look at it. DNNs analyze this data to offer practical information on the health of crops, growth circumstances, and probable factors causing stress. This empowers farmers to make well-informed choices immediately. This technology promotes the accuracy of crop management, optimizes resource efficiency, minimizes waste, and boosts total agricultural production. Using the IoBT, DNNs may dynamically adjust to fluctuating environmental circumstances, guaranteeing the highest possible agricultural output and long-term viability in SA methodologies.

Results and discussion

Experimental and simulation results: Once the platform was established, tomato plants were cultivated inside the laboratory. Proper aeration and illumination are necessary for the growth of tomato plants. The laboratory was adequately air-conditioned but lacked sufficient openings for sufficient air circulation. The development of tomato plants may be categorized into many phases: 1) germination and preliminary development with early leaves, 2) vegetative phase, 3) blooming period, 4) embryonic ripening period, and 5) peak ripening phase (Ge et al. 2021). Nevertheless, as shown by the study (Shamshiri et al. 2018), it is clear that the specific timing of every phase is contingent upon different types and several factors related to the environment, including soil quality, ambient temperature, vital nutrients, and illumination (Mumtaj Begum 2022).

The seeds were sown in cultivation plates and incubated for the first germination period of approximately ten days. Figure 3(a) depicts the progressive stages of germination of the plants within the controlled laboratory setting, presented in a logical sequence. Once the germination phase was over, the healthy seedlings were transferred to four planting containers. A structure equipped with sensors was then set up to collect information regarding the soil and atmospheric conditions, as seen in Figure 3(b). The primary tomato plant was located in the center pot, while the plants in the other containers served as backups in case any issues arose with the primary plant. Additionally, these plants were utilized to validate the results of the experiment. The middle pot has integrated sensors for measuring water in the soil, pH, temperature, and acoustic data. The other sensors are positioned on the roof of the planting station. Before the execution, all the sensors underwent validation and preliminary testing.

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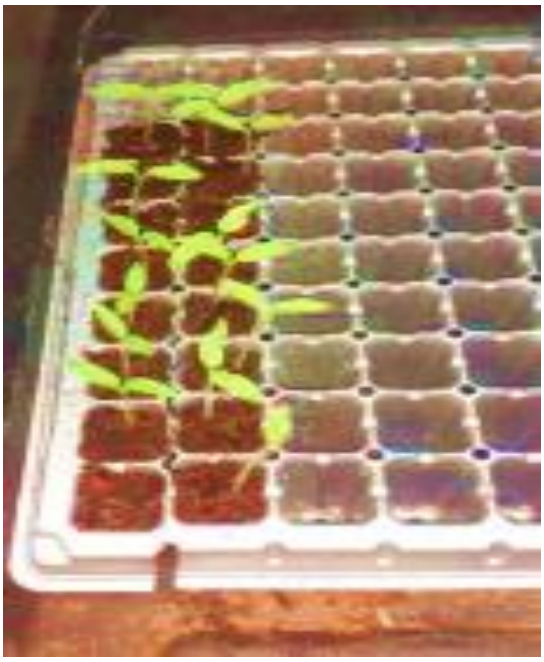
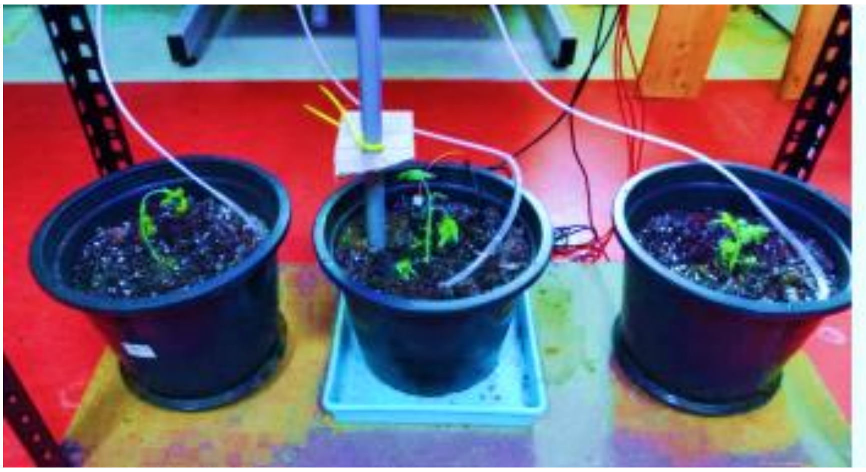


(a) **Germination phase**



(b) **Vegetative phase with bio-sensors**

Figure 3. R-CMM experimental setup with bio-sensors

The simulation is run on an Intel (R) Core (TM) i5-3570S CPU processor with a clock frequency of 3.10 GHz using the MATLAB program. The R-CMM system's usefulness is proven by checking and measuring error rates and how well it finds things. Currently, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and the proposed DNN are the comparison methods used (Mumtaj Begum 2022). Figure 4 shows the error rate and accuracy (%) of different deep learning algorithms for R-CMM in SA. With an accuracy rate of 83.56% and an error rate 0.2456, the DNN algorithm is the most accurate DL method for R-CMM in SA. An error rate of 0.4195 means that the SVM is correct 74.5% of the time. The KNN algorithm, on the other hand, is only 72.13% accurate and has a 0.4897 error rate. This means DNN is much more reliable and accurate for this R-CMM use case than the other DL methods.

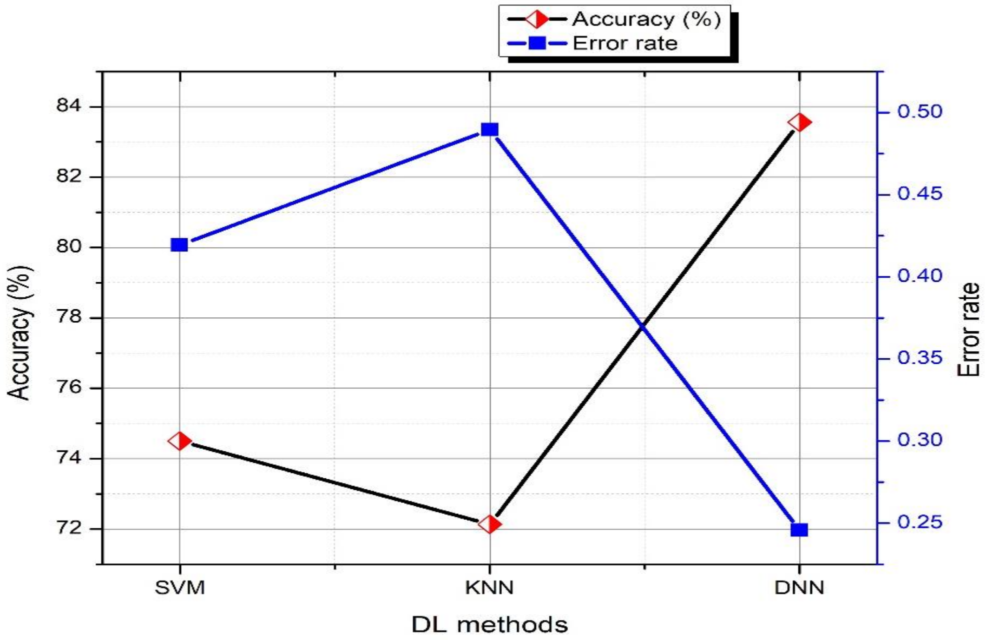


Figure 4. Accuracy (%) and error rate of various DL algorithms for R-CMM in SA.

Conclusions: With DNN, IoT, and BT, this study suggests R-CMM in SA. IoBT is a new network structure that uses small, renewable, and unnoticeable sensors to collect and study biological signals in the nearby area. This study showed an affordable IoT platform with sensors designed specifically for R-CMM operations in a tomato plantation in the lab. With an accuracy rate of 83.56% and an error rate of 0.2456, the DNN algorithm is the most accurate DL method. The study shows how important it is to be aware of your surroundings. The results of this study are likely to have a significant effect on pushing for and supporting the integration of SA and BT solutions. The goal of these solutions is to boost quality and efficiency while also promoting sustainability.

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Conflict of Interest: There is no conflict of Interest.

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ادغام اینترنت اشیا و بیوتکنولوژی برای نظارت و مدیریت در زمان واقعی محصول در کشاورزی هوشمند

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چکیده

هدف: مشکلات مدرن از جمله افزایش تقاضای غذا، منابع محدود، و تخریب محیط زیست را می‌توان به طور موثر از طریق عمل انقلابی کشاورزی هوشمند (SA) حل کرد. پاسخگویی به تقاضای جهانی و در عین حال کاهش اثرات زیست محیطی چالشی برای شیوه‌های کشاورزی سنتی است. ترکیب بیوتکنولوژی (BT) با SA یک راه حل انقلابی با تقویت روش‌های کشاورزی، افزایش بازده محصول و کاهش مصرف منابع ارائه می‌کند.

مواد و روش‌ها: ادغام سیستم‌های کشاورزی هوشمند از تجزیه و تحلیل داده‌ها و شبکه‌های عصبی عمیق (DNN) پتانسیل بهینه‌سازی کشاورزی را حتی بیشتر افزایش داده است. به منظور بهبود مدیریت محصول، کاهش ضایعات و افزایش تولید کلی مزرعه، کشاورزان می‌توانند از تصمیمات مبتنی بر داده استفاده کنند که توسط الگوریتم های DNN ممکن شده است تا بینش عملی در مورد سلامت محصول، روند رشد و شیوه‌های کشاورزی ایده آل به دست آورند.

نتایج: یک سیستم نظارت و مدیریت محصول در زمان واقعی (R-CMM) که DNN، اینترنت اشیا (IoT) و بیوتکنولوژی (BT) را یکپارچه می‌کند در این تحقیق به عنوان یک کاربرد کشاورزی هوشمند پیشنهاد شده است. IoBT با جمع‌آوری سیگنال‌های بیولوژیکی از محیط با استفاده از حسگرهای کوچک، تجدیدپذیر و غیر تهاجمی، داده‌های بلادرنگ را در مورد سلامت گیاه، شرایط خاک و پارامترهای آب و هوایی ارائه می‌کند. با این کار، مدیریت خودکار سیستم‌های محصول و نظارت مستمر از راه دور هر دو امکان پذیر می‌شود و هزینه‌های پرسنل را کاهش و کارایی کلی را افزایش می‌دهد.

نتیجه‌گیری: مدیریت مزارع داخلی به تعدادی از ویژگی‌های حیاتی، از جمله دما، رطوبت، رطوبت خاک و شدت نور متکی است که سیستم R-CMM از همه آنها برای حفظ کنترل استفاده می‌کند. استفاده از الگوریتم‌های DNN در این پلتفرم با پیش‌بینی زمان استرس، بهینه‌سازی تخصیص منابع و شناسایی نشانه‌های اولیه بیماری یا هجوم آفات، کشاورزی مؤثرتر و دقیق‌تر را امکان‌پذیر می‌سازد.

واژه‌های کلیدی: اینترنت اشیاء زیستی، بیوتکنولوژی، حسگرها، شبکه‌های عصبی عمیق، کشاورزی هوشمند

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