Towards Sustainable Future: A Review of Emerging Technologies in Controlled Environment Agriculture

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Abstract

The increasing global population and the rising demand for food and water are critically challenged by the shrinking amount of arable land caused by urbanization. A paradigm shift towards innovative agricultural practices becomes vital for solving these issues. These practices must boost production and make optimal use of limited land resources. In the literature, researchers have proposed Controlled Environment Agriculture (CEA) as one of the promising solutions to this complex problem. CEA is a method of farming fruits, vegetables, herbs, and other plants in controlled environments. In these environments, plant growth factors such as water, temperature, humidity, light intensity, ventilation, CO_2, O_2, nutrients, etc., are precisely regulated to optimize yield. While CEA methods offer significant advantages in productivity, they face challenges such as operational complexity and high energy consumption, which limit their scalability. To address these issues, researchers are increasingly integrating technologies like Internet of Things (IoT), Machine Learning (ML), Deep Learning (DL), Artificial Intelligence (AI), and Blockchain to enhance CEA efficiency and productivity. This review article examines recent advancements in CEA, emphasizing the role of these technologies in optimizing agricultural processes, reducing environmental impact, and advancing global food security. Finally, this paper explores limitations in current research and discusses emerging trends that could shape the future of CEA.

Keywords: Internet of Things, Machine Learning, Deep Learning, Artificial Intelligence, Smart farming, Controlled Environment Agriculture, Vertical Farming, Blockchain.

1. Introduction

With a projected global population of 9.2 billion by 2050 (Friedman & Mandelbaum, 2011), the demand for food is expected to surge, requiring sustainable solutions to meet these needs without further strain on natural resources (Shaw, 2007). Sixty to seventy percent more food will need to be produced by 2050 than today's (José Graziano, n.d.; Silva, 2018). Simultaneously, urban expansion and environmental degradation are reducing available arable land, intensifying the need for agricultural systems that optimize limited space. According to the current statistics, 55% of the world's population lives in urban areas, which is expected to grow to 70% by 2050. On the other hand, due to changes in lifestyle and improving infrastructure, food consumption will also increase and pressure on the arable lands (Silva, 2018). Even though increasing arable lands is a logical solution, it will not be practical because deforestation introduces new environmental issues, and soil health is declining due to sea level rise, erosion, and pollution (Foley et al., 2005).

In response to this pressing dilemma, there should be a sustainable way to produce more food with less land (Mueller et al., 2012; V. Singh & Misra, 2017).

Considering these challenges, Controlled Environment Agriculture (CEA) has emerged as a viable solution, providing a method to increase food production within limited space by regulating environmental factors that affect plant growth. CEA encompasses two primary methods: Hydroponics and Aeroponics. These methods accommodate various crops, including fruits, leafy vegetables, cereals, herbal plants, and flowers (Ragaveena et al., 2021). Hydroponics involves growing plants in nutrient-rich solutions instead of soil, usually in tunnels or tank-like containers where the solution circulates through the roots (Mamatha & Kavitha, 2023; Sambo et al., 2019; Velazquez-Gonzalez et al., 2022). In contrast, Aeroponics, a subset of hydroponics, involves spraying the nutrient solution around the plant roots to make a mist rather than submerging them (Lakhiar et al., 2018; Min et al., 2023).

Beyond Hydroponics and Aeroponics, other CEA techniques include Aquaponics (Kloas, n.d.; Perla, 2021), Biophonic (Gartmann et al., 2023), and Vertical Farming (Shamshiri et al., 2018). Aquaponics integrate aquaculture (fish farming) with Hydroponics, with fish waste providing plant nutrients and vice versa. Biophonic combines the elements of Aquaponics and organic Hydroponics to enrich the nutrient solution with fully organic matter. Vertical farming stacks plant layers vertically, optimizing space usage and boosting crop output (Oh & Lu, 2023; Saad et al., 2021).

CEA is an ever-evolving industry characterized by ongoing technological innovations that offer clear advantages over traditional agriculture (Geoponics) (Ragaveena et al., 2021). Initially, it enables fresh and nutrient-rich crop production year-round, as external weather conditions do not affect production, and automated monitoring and control systems facilitate strict control over environmental conditions (Niu & Masabni, 2018). CEA systems surpass traditional soil-based farming regarding crop productivity per unit of space and mitigate soil-borne pathogens, resulting in robust crop health, increased yields, and reduced pesticide dependence (Ragaveena et al., 2021).

In addition, CEA efficiently utilizes vertical space, addressing concerns related to land scarcity, and exhibits the potential to diversify crops beyond just leafy greens and microgreens. Since technology is employed to manage the farming environment, and modern Artificial Intelligence (AI) enabled systems can provide expert advice to farmers, even individuals not specialized in agriculture can invest and participate in farming (Ragaveena et al., 2021). Furthermore, due to closed-loop water systems, water consumption in CEA is drastically reduced (Oh & Lu, 2023) and mitigates most environmental problems in traditional farming methods.

Despite its advantages, CEA faces challenges such as high initial costs, operational complexity and high energy demand, (Oh & Lu, 2023). Figure 1 depicts the major challenges in CEA. To overcome these, researchers are integrating Internet of Things (IoT), AI, Machine Learning (ML), and Blockchain to improve efficiency and reduce resource use. (Liu et al., 2022; Srivani et al., 2019).

Figure 1: Major challenges in CEA

This study provides a comprehensive review of recent research on the integration of IoT, AI, ML, Deep Learning (DL), and Blockchain in CEA. The primary aim is to evaluate how these technologies are applied in modern CEA systems and to assess their effectiveness in addressing critical challenges within the field. Through this review, several key gaps in the current literature were identified, showing the need for continued research to advance CEA. By overcoming the limitations inherent in traditional farming methods, these emerging technologies hold significant potential to transform agriculture, promote sustainable food production and enhance food security worldwide.

The rest of the paper is organized as follows: Section 2 summarizes the reviewed papers into a table in terms of technology utilization in CEA. Section 3 reviews the available literature under four subsections, namely the impact of IoT in CEA, AI innovations in CEA, Blockchain in CEA, and the synergy of technologies in the field. Then, in Section 4, we discuss existing research, research gaps, potential future developments in the field, and emerging advancements in technology for CEA. Finally, Section 5 concludes our work with a summary.

2. CEA Technology Integration and Advances

In CEA, cutting-edge technologies are employed to address contemporary challenges. Innovations such as precision agriculture, AI, and the IoT optimize plant growing conditions. Advanced LED lighting and hydroponic systems enhance crop productivity through the integration of sensor networks, ML, and DL. These advancements in CEA address the limitations of traditional agriculture by improving sustainability and productivity.

This review paper has meticulously consolidated nearly fifty research papers about technology integration in the CEA. In our thorough investigation, we reviewed the selected papers to understand how advanced technologies are employed in the field. Technologies such as IoT, ML, DL, Fuzzy Logic (FL), Expert Systems (ES), Genetic Algorithms (GA), Computer Vision (CV) and Blockchain are increasingly being employed in the field. Table 1. presents the utilization of these technologies in some of the reviewed works.

Table 1: Technology utilization in existing research related to CEA

Research	IoT	ML	DL	FL	ES	GA	Other AI	BC	CEA Method	Remarks
(Ragaveena et al., 2021)	✓	✓	✓	✓					Many	Review
(Kerns & Lee, 2017)	✓								Aeroponic	
(Marques et al., 2019)	✓								Hydroponic	Mobile App
(Liu et al., 2022)	✓	✓	✓	✓	✓	✓		✓	Employed a closed-loop production principle	
(Cohen et al., 2022)		✓	✓		✓	✓			Dynamically controlled environment agriculture	
(Prasetia et al., 2021)	✓								A combination of LED grow lights, natural light, and hydroponics to grow plants	
(Shrivastava et al., 2021)	✓	✓	✓						Vertical hydroponic farming	
(Kaur et al., 2023)	✓								A combination of LED grow lights, natural light, and hydroponics to grow plants	
(Srivani et al., 2019)	✓	✓	✓	✓	✓	✓		✓	Hydroponics	
(Hegedűs et al., 2023)	✓	✓							Uses a combination of LED grow lights, natural light, and hydroponics to grow plants.	SARSA and MAPE-K
(Yusuf et al., 2023)	✓								Indoor vertical farming system	ThingsSentral
(Yasrab et al., 2021)		✓	✓						Predicting plant growth in CEA	
(Oh & Lu, 2023)	✓								Vertical-urban agriculture	Review
(Morella et al., 2023)	✓								Vertical farming	
(Hwang et al., 2022)		✓	✓						Use of color images captured by a camera for crop growth monitoring in vertical farms	

(Y. Lu et al., 2023)	✓	✓	✓						Predicting growth of strawberries in CEA	
(Tavan et al., 2021)	✓								Irrigation management in a soilless vertical farm	
(Ojo & Zahid, 2022)		✓	✓						Greenhouse, plant factory, and vertical farm	Review
(Alhnaity et al., 2020)		✓	✓						Greenhouse plant growth and yield prediction	
(Mokhtar et al., 2022)		✓	✓						Hydroponically grown Lettuce yield prediction	
(C.-P. Lu et al., 2019)	✓	✓	✓				CV		Growing mushrooms in greenhouses	
(Joshi et al., 2023)		✓	✓						Use of DL for crop mapping and yield prediction	Remote sensing, Review
(Sun et al., 2019)		✓	✓						Soybean yield prediction	
(Madhavi et al., 2022)		✓							Growing strawberries in a greenhouse	
(Gong et al., 2021)		✓	✓						Greenhouse crop yield prediction	
(Dutta et al., 2023)	✓								Hydroponics in a vertical farming environment	
(Xiong et al., 2020)	✓							✓		
(Hossain et al., 2023)	✓	✓						✓	Smart agriculture	
(Kassim, 2022)	✓							✓	Smart agriculture	
(Maya Olalla et al., 2023)							FL		Hydroponic in greenhouse	Fuzzy Logic
(Thomopoulos et al., 2024)	✓						FL		Hydroponic in smart greenhouse	Fuzzy Logic
(Bautista et al., 2023)							GP		Aquaponic	Genetic Programming
(de Ocampo & Dadios, 2017)							GA		Energy optimization in a smart farm	Genetic Algorithm
(Dawn et al., 2023)	✓	✓					ES			Expert Systems

In the next section, we present a comprehensive review of technologies and their applications in CEA, along with their limitations.

3. Comprehensive Review on Technology Integration in CEA

The primary focus of this review is on the use of technologies such as IoT, AI, ML, DL, FL, ES, Blockchain, and other AI-related technologies in CEA, particularly their efficacy in addressing challenges within this domain. This section defines the relevance of each technology to CEA, discusses its utilization, evaluates its capacity to produce desired outcomes, and examines how individual technologies and their combinations serve the field.

3.1. Impact of IoT in CEA

IoT refers to the interconnected network of physical devices, sensors, software components, software platforms and other technologies that collect and exchange data to enable smart and automated processes over a network or Internet.

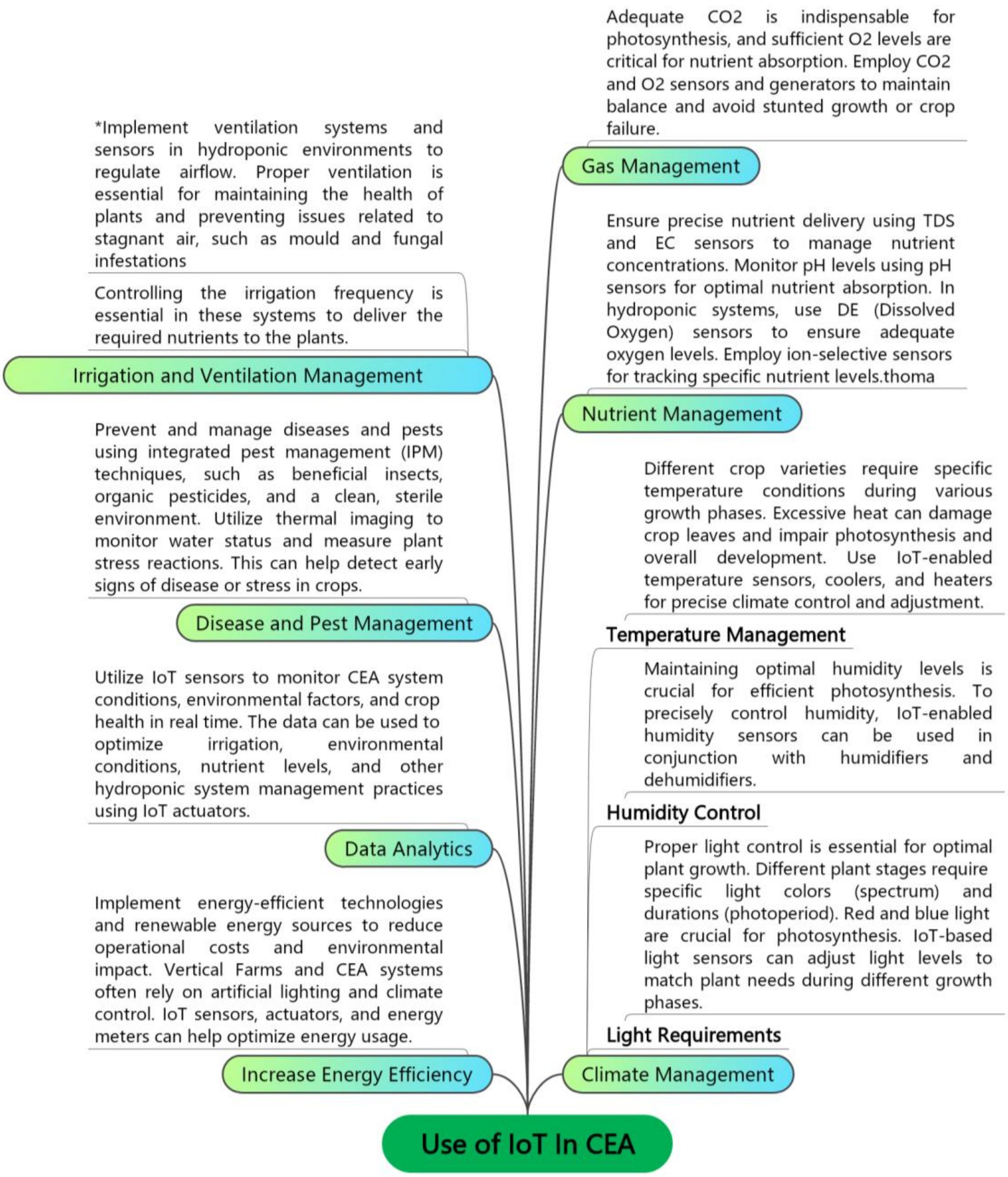

Figure 2: Use of IoT in CEA

According to literature, in CEA, IoT plays a significant role by providing real-time monitoring and control of environmental variables related to plant growth within indoor farming facilities (Atmadja et al., 2022; Dim & Guillermo, 2022; Kaur et al., 2023; Kerns & Lee, 2017; Liu et al., 2022; Marques et al., 2019; Ragaveena et al., 2021; Shrivastava et al., 2021; Yusuf et al., 2023; Zhang et al., 2022). Figure 2 shows the various management tasks performed using IoT in CEA.

Integrating IoT technologies into soilless farming practices offers a paradigm shift from conventional agricultural methods. Sensors, actuators, and smartphone applications have improved farming practices, enabling individuals without specialized agricultural knowledge to engage in efficient crop cultivation (Ragaveena et al., 2021).

Several studies have introduced innovative aeroponic and hydroponic systems, integrating IoT capabilities for real-time monitoring and autonomous control (Kerns & Lee, 2017; Marques et al., 2019; Shrivastava et al., 2021). These systems leverage sensor networks and mobile applications to manage crucial environmental variables such as temperature, humidity, pH levels, and nutrient concentrations.

IoT sensors monitor growing medium conditions, environmental conditions, and crop health in real-time (Yadav & Swamy, 2022). These sensors encompass a diverse range, including temperature sensors for precise climate control, humidity sensors to maintain optimal moisture levels, light intensity sensors for accurate lighting adjustments, pH sensors for monitoring soil acidity, TDS (Total Dissolved Solids) and EC (Electrical Conductivity) sensors for managing nutrient concentrations, DE (Dissolved Oxygen) sensors to ensure adequate oxygen levels in hydroponic systems, ion-selective sensors for tracking specific nutrient levels, leaf temperature sensors for monitoring plant health, dielectric sensors for moisture measurements, thermal imaging for water status and measure stress reactions and imaging sensors for assessing crop development and identifying potential issues(Ragaveena et al., 2021; Tavan et al., 2021).

Using IoT actuators, the sensor data can then optimize irrigation (Shrivastava et al., 2021), environmental conditions, nutrient levels, and other crop management practices (Aliac & Maravillas, 2018). By harnessing the data generated by these sensors, CEA systems deploy IoT-based actuators to fine-tune environmental conditions and crop management practices (Kaur et al., 2023; Shrivastava et al., 2021). These actuators include cooling systems and heating systems to properly control the temperature, ventilation systems to control humidity, and lighting controls that adapt to the plants' changing needs (Verma, n.d.). Further, automated irrigation systems adjust water delivery based on requirements in indoor farming systems or soil moisture readings (Velazquez-Gonzalez et al., 2022), and nutrient-dosing systems maintain optimal nutrient levels (Dhal et al., 2022). The work done by (Marques et al., 2019) has incorporated IoT-enabled actuators to ensure precise administration of nutrients and water, in return optimizing crop productivity.

Notably, literature shows that IoT-enabled systems showcase enhanced crop production, resource efficiency, and significant advancements in vertical farming (Atmadja et al., 2022; Kaur et al., 2023; Yadav & Swamy, 2022). Automated vertical farming systems supported by IoT sensors and actuators demonstrate improved growth conditions, resulting in higher yields and optimal nutrient delivery (Kaur et al., 2023; Shrivastava et al., 2021). Additionally, studies indicate the potential for IoT-based systems to ensure year-round production of unique crops, fostering sustainability in agriculture (Yadav & Swamy, 2022).

While IoT integration presents promising opportunities, challenges persist. More accurate sensors, energy consumption, and scalability require further exploration (Atmadja et al., 2022; Kaur et al., 2023). Additionally, research emphasizes the importance of real-time monitoring for nutrition solutions and pest management in controlled environments to optimize production (Marques et al., 2019; Ragaveena et al., 2021).

Emerging concepts, including the utilization of edge computing, AI, and forthcoming 5G technology, are poised to redefine smart farming (Liu et al., 2022). These advancements aim to streamline data analysis, optimize plant growth systems, and establish high-performance communication infrastructures, which are crucial for the evolving CEA industry.

3.2. AI innovations in CEA

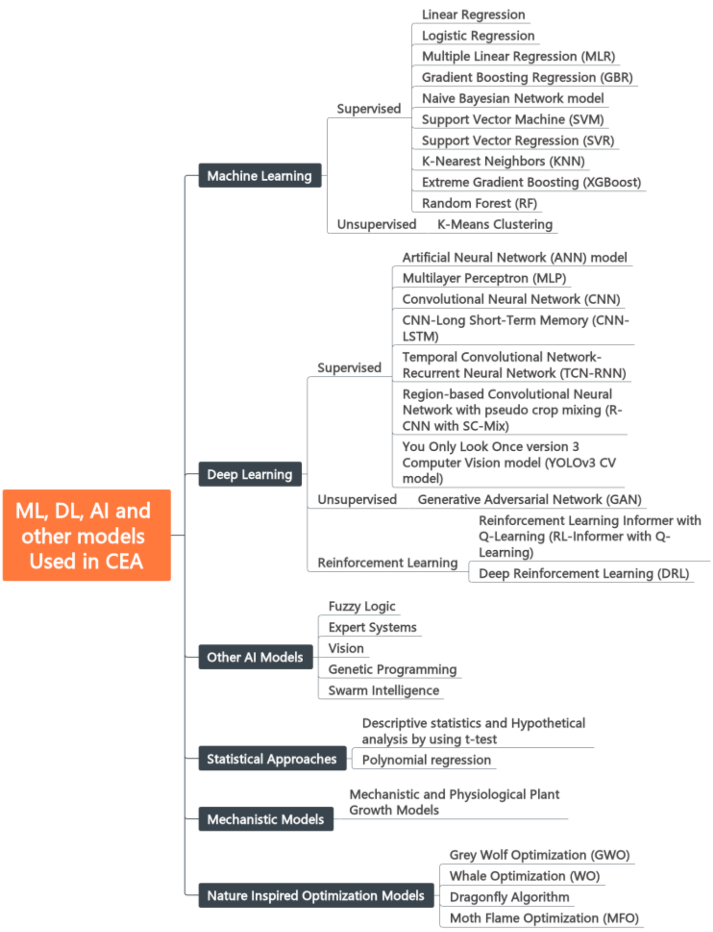

Figure 3: ML, DL, AI, and other models employed in CEA

AI is a broader field of computer science that aims to create machines or software systems that can perform tasks that typically require human intelligence or are sometimes beyond human capabilities, such as making predictions, understanding natural languages, recognizing patterns in a large dataset, and making rational decisions.

The leading AI technologies and algorithms such as ML, DL, FL, ES, GP (Bautista et al., 2023), CV (C.-P. Lu et al., 2019) and Robotics can be directly employed in CEA operations to make the systems more responsive, dynamic, and efficient in all ways. By looking at the literature, it has been noticed that ML and DL have become the widely studied technologies in this field. According to our research, Figure 3 depicts the ML, DL, AI and other models employed in CEA.

3.2.1. Use of ML and DL in CEA

ML and DL are subsets of AI, focusing on creating algorithms and models that enable machines to learn from data, recognize patterns, and make predictions or decisions without being explicitly programmed (Federchuk, 2022; Usharani et al., 2022). DL is a specialized branch of ML that employs Artificial Neural Networks (ANN) with multiple hidden layers (Sarker, 2021a). DL can automatically extract high-impact features and patterns from large datasets, while ML must have some kind of domain expertise to select features from datasets for constructing models (Taye, 2023). However, in terms of resource utilization, DL needs more computing power and extensive training data compared to ML (techstudycell, n.d.). ML models find applications in various fields, such as regression, classification, clustering, and recommendation systems (Sarker, 2021b), while DL excels in tasks like image and speech recognition, as well as natural language processing (NLP), particularly in contexts involving extensive unstructured data (Alzubaidi et al., 2021).

ML and DL have been recently applied in CEA for predictive modeling, correlation analysis, offering solutions for microclimate prediction, crop growth monitoring, crop forecasting, stress detection, irrigation, and energy-efficient controls (Ajagekar et al., 2023; C.-P. Lu et al., 2019; Ojo & Zahid, 2022; Srivani et al., 2019). They analyze large datasets such as environmental conditions and crop data, enabling the identification of diverse patterns, trends and correlations between various environmental factors related to plant growth and the identification of diseases (Ojo & Zahid, 2022). Further, the trained models process real-time data and control the environment. These models play a pivotal role in detecting crop-related issues, including diseases and suboptimal growth (Ojo & Zahid, 2023; V. Singh & Misra, 2017). Moreover, they are utilized to ensure the maintenance of optimal conditions to maximize yield and quality (Srivani et al., 2019). Various ML and DL algorithms, both established and recent advancements, are being employed in this domain to analyze data and extract valuable information.

Commonly employed ML algorithms include Naive Bayes, Support Vector Machines (SVM), K-Nearest Neighbors (K-NN), K-Means Clustering, Fuzzy Clustering, Gaussian Mixture Models (GMM), Ensemble Learning, Extreme Gradient Boosting (XGB) and Random Forest (RF) (Mokhtar et al., 2022; Srivani et al., 2019).

ML techniques, such as linear regression, SVM, logistic regression, and ANN, have been applied to predict plant growth rates considering environmental variables, ensuring optimal conditions in hydroponic systems in work done (Srivani et al., 2019). According to work done by (Madhavi et al., 2022), ML models, particularly GBR, have performed well in predicting strawberry leaf colour based on soil parameters and plant age, aiding in optimizing growth conditions.

DL goes beyond traditional ML by using complex models and boosting classification accuracy or minimizing errors in regression tasks, provided sufficient large-scale datasets are available for training (Alhnaity et al., 2020). Techniques such as Deep Artificial Neural Networks (DNN), Convolutional Neural Networks (CNN) (C.-P. Lu et al., 2019), ResNet (a type of CNN), Generative Adversarial Networks (GAN) (Yasrab et al., 2021), R-CNN (Hwang et al., 2022), CNN-LSTM, TCN-RNN and RL-Informer (Y. Lu et al., 2023) are among the frequently utilized DL models.

In the project AgrarSense (Hegedűs et al., 2023) have developed a scalable IoT framework that employs federated learning, enabling autonomous operation in grow boxes. ML techniques like SARSA and MAPE-K regulate farm conditions autonomously, enhancing energy efficiency and data management. Utilizing DL like FutureGAN, the study (Yasrab et al., 2021) showcases the efficiency of image analysis in predicting plant growth patterns and accelerating experimental cycles by reducing cultivation and measurement time. Novel techniques like SC-Mix combined with Mask R-CNN models offer improved crop segmentation in vertical farms, facilitating more precise growth monitoring (Hwang et al., 2022). An innovative approach using reinforcement learning and time-series prediction models aims to optimize the cultivation environment continuously, significantly improving strawberry yield (Y. Lu et al., 2023). Various DL models, including CNN-LSTM, have been employed for crop yield prediction, utilizing growth and environmental variables and offering accurate predictions for soybean and strawberry yields (Joshi et al., 2023). DL classifiers like ResNet-50 have been applied to detect plant diseases, with GAN-based resampling strategies improving classification accuracy significantly (Ojo & Zahid, 2023). According to the work done by (Gong et al., 2021), advanced DL techniques like TCN-RNN have outperformed traditional ML and DL methods in predicting greenhouse crop yields.

A systematic review by (Ojo & Zahid, 2022) highlights the prevalence of DL applications in greenhouses, emphasizing the potential for future advancements such as recurrent neural networks (RNNs) and unsupervised learning using GANs.

Both ML and DL find applications in predictive modeling, microclimate prediction, crop monitoring, and quality control in CEA. They play a crucial role in addressing issues related to crop health and ensuring the conditions necessary for maximum yield and quality. Many algorithms, from Naive Bayes to advanced DL models like CNNs and GANs, are being deployed to process and generate data in CEA.

3.2.2. Use of other AI technologies in CEA

In addition to ML and DL, AI technologies such as FL, CV, GA, GP, Swarm Intelligence (Sharma et al., 2022), and ES have been employed in CEA (Dawn et al., 2023).

A fuzzy control method has been used to improve hydroponic strawberry cultivation in a greenhouse, significantly enhancing plant growth and fruit size compared to traditional irrigation systems (Maya Olalla et al., 2023). (Thomopoulos et al., 2024), implementing a fuzzy logic controller for optimising greenhouse-based plant production shows the importance of intelligent control systems in agriculture, emphasising their role in enhancing plant growth by considering critical atmospheric factors.

CV is another technology utilised in CEA. The literature contains numerous applications for CV, including those related to growth monitoring, fruit detection, flower detection, counting fruits and plants, determining maturity levels, and detecting pests and diseases (Luo et al., 2023).

GAs are also employed in smart farming to optimise resource allocation, such as water and energy, for irrigation and crop management, enhancing agricultural efficiency and sustainability (de Ocampo & Dadios, 2017; Santiago et al., 2017; Valenzuela et al., 2018). Further, GA is also used in image segmentations (Niu & Masabni, 2018) and data preprocessing stages in ML and DL.

GP and bio-inspired algorithms have also been utilised to optimise artificial light properties, minimise evapotranspiration, and improve lettuce growth (Bautista et al., 2023).

Even though there is minimal discussion of the use of Expert Systems in CEA, the application of Expert Systems in this field is a promising area that can significantly enhance crop health and disease management, irrigation and nutrient management, efficiency and productivity (Dawn et al., 2023).

Overall, a diverse array of the above-mentioned AI technologies proved to be valuable tools in advancing the efficiency and productivity of CEA. While some of these technologies are relatively less discussed in the context of CEA, their potential for enhancing various aspects of crop management, resource optimisation, and decision support signifies an exciting frontier in the future of CEA.

3.3. Blockchain in CEA

Blockchain is a decentralized and tamper-resistant digital ledger (a record-keeping system that is extremely difficult to change or manipulate without anyone noticing) that can record and track every step of the agricultural production and distribution process (Kamilaris et al., 2019). It offers transparency, traceability, and security, ensuring that the data regarding nutrients, fertilizers, and chemicals is accurately recorded and cannot be altered without consensus (Harini et al., 2023). It has various applications, including agricultural insurance, smart farming, food supply chain transparency, and streamlined agricultural product transactions, making agriculture smarter, safer, and more efficient (Kassim, 2022). Blockchain technology shows the potential to enhance traceability, transparency, and trust in agricultural supply chains but faces challenges in smallholder participation and integration complexity (Mehare & Gaikwad, 2023; Xiong et al., 2020). Moreover, integrating Blockchain technology into CEA is one of the most outstanding achievements in this field (Xiong et al., 2020).

The work done in AgriBlockIoT (Caro et al., 2018), a blockchain-based solution, integrates IoT devices within an agricultural food supply chain to provide secure traceability and has been evaluated using Ethereum and Hyperledger Sawtooth blockchains to analyze performance metrics such as latency, CPU, and network usage, while identifying their respective advantages and disadvantages. In (Lin et al., 2018) the authors have combined blockchain and IoT technologies to create a decentralized and automated food traceability system. This approach minimizes human intervention by using IoT devices for recording and verification and employs smart contracts to enable law enforcement to detect and resolve issues.

The utilization of Blockchain technology is relatively new in the field, and because of that, there is a minimal number of publications available. Since Blockchain technology increases traceability, food safety, and consumer trust, major companies like Walmart and Alibaba are actively implementing it in their process (Dey & Shekhawat, 2021; Xiong et al., 2020). Blockchain technology has also been used in improving data security in IoT networks as it provides a way to maintain data integrity using hash validation (Ahmed et al., 2022; Hossain et al., 2023).

3.4. Synergy of technologies CEA

The existing literature reveals a prevalent trend where research efforts often involve integrating multiple technologies (Liu et al., 2022; Shrivastava et al., 2021; Srivani et al., 2019). Within the scope of our selected literature, many research studies demonstrate a combination of IoT, ML, and DL technologies (C.-P. Lu et al., 2019; Y. Lu et al., 2023). In contrast, few works explore the synergies between IoT, ML, DL and Blockchain technologies (Hossain et al., 2023; Mehare & Gaikwad, 2023; Xiong et al., 2020).

Moreover, Blockchain technology is employed to enhance transparency, security, and traceability in the CEA systems as well as the supply chain (Ali et al., 2022; Liu et al., 2022; Mehare & Gaikwad, 2023; Srivani et al., 2019). It allows for secure communication and record-keeping of every production stage, from planting to distribution (Farooq et al., 2023; Radeva & Popchev, 2022; Vangala et al., 2021); this ensures the integrity of organic or sustainable certifications and provides consumers with a clear understanding of the origin of agri-food products they purchase.

Further, integrating these technologies into the CEA introduces new challenges, such as integration complexity, potential expertise shortages, the high cost of technologies and devices, and concerns related to data security.

4. Discussion

As per the survey, smart CEA involves three main types of research. First, IoT and automation technologies maintain threshold levels of growth factors in systems. Second, researchers refine parameters/factors using IoT, ML, and AI for optimal plant growth. Third, ML and DL models predict crop yield and diseases, advancing AI.

4.1. Existing Research

Some researchers use IoT and other environmental monitoring and automation technologies to maintain acceptable threshold levels of growth factors within CEA settings; this is achieved through the automation of various actuators like pumps, which regulate factors such as temperature, humidity, lighting, and nutrient compositions. Furthermore, these systems promptly dispatch real-time notifications to alert farmers, facilitating timely responses and necessary adjustments. In this type of research, threshold levels have been set based on the currently available knowledge and experience.

Moreover, in the second type of research, researchers work on the collected data in the CEA environments to refine system parameters and calibration on growth factors to make the growth of the plants healthy and efficient in CEA. In literature, most researchers employ IoT to collect data, ML and other AI technologies, Mechanistic and physiological plant growth models, and hybrid approaches to find optimal plant growth conditions. Further, different actuators were used to optimize the growth environments to achieve more efficient results in real-time.

In the third type of research, researchers have worked on different ML and DL models for predicting crop yield, growth rate, and disease identification and finally invented novel DL algorithms to better the overall development of the AI field. For example, they use the SC-Mix data augmentation technique with an R-CNN deep learning model in their work (Hwang et al., 2022).

Furthermore, in the review, it has been noted that DL models perform well in most applications compared to ML. However, hybrid DL models outperform individual models. For instance, hybrid models like CNN-LSTM outperform the individual CNN and LSTM models (Sun et al., 2019), and TCN-RNN outperforms individual TCN and TNN models (Gong et al., 2021).

4.2. Research gaps

In the review, a set of research gaps has been identified as outlined below. Addressing these gaps is important to overcome future challenges in CEA automation and enhance the feasibility of the plant factory concept.

- **Data Repository and Standardized Collection:** A shared and collective database will enable comparative studies, restructure the data analysis and facilitate a platform of knowledge sharing among the researchers. Centralized data warehouses and homogeneous data collection platforms are lacking as well.
- **Fragmented Research Efforts:** CEA research study is mostly done in isolation, which limits the opportunities for collective knowledge development. To develop dedicated data analysis tools or cloud-based services that aggregate findings and provide integrated solutions for plant growth optimization, a centralized, collaborative approach is necessary.
- **Reliable Long-Term Sensor Technology:** Sensors used in this field are not durable and accurate over long periods of time, especially in fully automated environment scenarios. However, robust, precision sensors are needed to achieve autonomous, reliable systems.

- **Real-Time Nutrient and Pest Monitoring:** CEA efficiency would be dramatically improved by reducing the risk of nutrient imbalances and pest outbreaks by improving the real-time monitoring.

4.3. Potential future developments in CEA technology

By examining the current developments in the field, the prospects for CEA are multifaceted. They encompass the development of more robust, real-time, dynamically controlled microclimate models to optimize plant growing environments, ultimately achieving higher yields at a lower cost. This includes enhancing artificial lighting systems to support photosynthesis across various plant varieties efficiently.

- **Dynamic Microclimate Models:** The use of real-time and adaptive models optimizes the plant growth conditions by changing the factors such as temperature, light, and humidity which result in the higher yields and quality of the crops.
- **Renewable Energy Integration:** By using renewable sources (e.g Solar), along with the water recycling process will reduce the CEA operational costs.
- **Blockchain for Transparency:** Using blockchain technology will improve security and transparency, which will ensure reliable data from production to distribution.
- **Enhanced Communication and AI:** Using IoT-based communication systems, CEA will be able to share real-time data and refine control with the expansion of 5G and high-speed data processing.

4.4. Emerging trends and advancements in technology for CEA

The rapid progress of communication technologies, including 5G and fibre networks, is set to play a pivotal role in facilitating the communication of cyber-physical systems like connected intelligent farms. Additionally, the ongoing advancements in data processing power, enabled by high-performance computing platforms and the accessibility of storage in the cloud at reduced costs, are collected to create substantial opportunities for the growth of DL technologies and emerging distributed AI platforms. As these technologies continue to advance, CEA is positioned to meet the growing global demand for food and contribute significantly to sustainable agriculture practices.

Overall, the existing research primarily focuses on integrating IoT, ML, DL, and AI technologies for real-time monitoring and precise control of environments, ensuring that optimal growth conditions are consistently maintained. They are also utilized to identify diseases early and accurately predict harvest yields. Additionally, Blockchain technology is being leveraged to enhance the security of IoT communications and introduce a new level of transparency to the various activities within crop production. In the future, it is imperative for research to centre on implementing closed-loop control systems for plant growth. These systems should utilize camera-based feedback mechanisms to adjust environmental conditions real-time. This approach can potentially enhance both efficiency and product quality while ensuring robust system management and meeting the demand in the market.

5. Conclusion

CEA is increasingly recognized as a critical solution to address challenges in global food production, driven by population growth, limited arable land, and environmental constraints. Although current CEA systems show potential to address food production concerns, there remains a need for extensive research in areas such as operational complexity, energy efficiency, agricultural production quality, crop selection, and more. This paper highlights the pivotal role of emerging technologies such as IoT for real-time monitoring, ML and DL for predictive analytics, and Blockchain for data transparency and traceability in advancing CEA systems.

To bridge existing gaps, future research should prioritize the establishment of centralized data repositories and standardized data collection platforms, which would foster knowledge sharing among researchers. Additionally, developing robust, durable sensors and improving real-time monitoring for nutrient and pest management are essential for scalable, automated CEA systems. Enhanced data analysis platforms, tools for plant phenotyping, and advanced imaging technologies will further enable CEA to meet the growing demand for sustainable agriculture solutions. Securing the necessary funding and support is critical for the development, maintenance, and expansion of this infrastructure, ultimately empowering researchers and stakeholders to refine CEA automation and the plant factory concept.

Finally, the insights and recommendations presented in this paper contribute to a globally relevant framework for addressing food security and sustainability through advanced agricultural technology.

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