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AI and IoT in Sustainable Agriculture: A Review

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Abstract

Artificial intelligence (AI) and internet of things (IoT) integration have transformed the world of sustainable agriculture, presenting new ways of resource optimization, increasing crop yields, and making environmental sustainability more accessible. The current literature review analyzes the applications of AI and IoT in three significant agricultural systems: aquaponics, hydroponics, and poultry farming. By critically analyzing recent studies, this paper emphasizes how deep learning-enabled computer vision techniques allow for the precise monitoring and management of greenhouse environments by overcoming issues like data scarcity and environmental variability. In addition, the review focuses on IoT-driven advancements in hydroponic and aquaponic systems, focusing on sensor integration, real-time data processing, and machine learning algorithms that predict nutrient requirements and optimize growth conditions. In the poultry farming context, the use of AI models in environmental control and disease detection can contribute to the reduction of labor dependency and the enhancement of animal welfare. The identified challenges include the need for domain-specific AI adaptations, robust security protocols for IoT infrastructures, and scalability of integrated systems. It further indicates future research directions, such as multi-modal sensor fusion, edge computing for real-time analytics, and user-friendly platforms that would make it accessible to a wider audience among farmers. Synthesizing the current advancements and the gaps in them, this paper provides researchers and practitioners with insights into how to utilize AI and IoT in agriculture for sustainability and efficiency.

Keywords: Artificial intelligence (AI), internet of things (IoT), sustainable agriculture, aquaponics, hydroponics, poultry farming, smart greenhouses, machine learning, precision agriculture, IoT-driven systems

INTRODUCTION

With increasing global food demands and rising climate change, resource depletion, and environmental sustainability concerns, the old ways of agriculture have had to change. Although conventional farming methods have been proven to be efficient over time, they are no longer effective in dealing with some of the new challenges such as land scarcity, water inefficiency, and labor dependency. This, with a rising population and increasing urbanization, has created a pressing demand for new methods of agricultural production than ever before [1].

Hence, sustainable agriculture has now emerged as one of the vital paradigms in such directions since this not only conserves resources for food production but also reduces adverse environmental impacts. Controlled environment agriculture, which

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includes aquaponics, hydroponics, and poultry farming, has thus got much attention under such a paradigm. Such systems provide scalable and resource-efficient alternatives to traditional farming by integrating plant and animal production within closed-loop systems. However, achieving the maximum efficiency and productivity of these systems would need advanced technologies to be integrated [2].

This represents a significant step toward the aforementioned goals through the integration of artificial intelligence (AI) and the internet of things (IoT) in agriculture. AI provides data-driven decision-making, predictive analytics, and automation, whereas IoT enables real-time monitoring and control through the interlinking of devices. In this context, they provide an opportunity for farmers to optimize resources, increase productivity, and achieve sustainability. For instance, in aquaponics and hydroponics, data from IoT sensors for pH, temperature, and humidity are collected and then analyzed using AI algorithms to determine actionable insights as well as automation of the process. Similarly, AI-driven models in poultry farming are used to establish control over the environment, detect diseases, and optimize feeds that would lead to improvement in animal welfare and efficiency in operation [3].

Another symbiotic combination in aquaculture and hydroponics is aquaponics, well known for utilizing AI and IoT in sustainable agriculture. Aquaponics systems may monitor real-time water quality, nutrient levels, and fish health through the use of IoT sensors and AI algorithms. Aside from the monitoring nutrient solutions and environment parameters, as in IoT-enabled conditions, other benefits for using AI-driven model predicting growth behavior of the crop and amount of nutrients that crop require, the agricultural components, and also called as crucial, poultry farm. In an IoT enabled/connected world control environmental conditions on poultry farms requires AI. To avoid biosecurity risks, dependency on labor may be minimized via AI and IoT. While the integration of AI and IoT into agriculture is of immense benefits, the challenges associated with its implementation are not yet negligible. These include heterogeneity in agricultural environments, security of data, and high implementation cost. Domain-specific AI models and robust IoT frameworks adapted to different agricultural systems remain a significant gap in research. A multidisciplinary approach with innovations in sensor technology, machine learning, edge computing, and cloud integration is needed to address these challenges [4].

This paper offers a detailed review of the application of AI and IoT in sustainable agriculture, with specific emphasis on aquaponics, hydroponics, and poultry farming systems. This research analyses the latest advancements that help in understanding how these technologies solve critical challenges, increase efficiency, productivity, and sustainability. This review identifies research gaps and outlines future directions to develop scalable, secure, and user-friendly systems. Following will be the arrangement of the structure of the paper: the ensuing section will talk about a specific detailed literature review along with the central innovations and its applications in aquaponics and hydroponics, and it will also discuss the poultry farming practice. Then some discussion on some challenges and their future directions followed by the probability of integrating with emerging technologies – multi-modal sensor fusion, edge computing, or blockchain for sharing data securely is discussed. The paper sums up key insights and highlights the transformative potential of AI and IoT in achieving sustainable agriculture [5].

Integration of AI and IoT in agriculture has drawn immense attention from research, practitioners, and policymakers. This convergence addresses the modern challenges for agriculture, promoting sustainable farming practices. AI and IoT facilitate data-driven decision-making, predictive analytics, and automation, allowing farmers to be optimum in resource allocation, to maximize productivity with the incorporation of sustainability. For example, in aquaponics and hydroponics, IoT sensors capture data on pH, temperature, and humidity that AI algorithms then analyze to produce actionable insights and automate processes. Similarly, AI-driven models are used in poultry farming to regulate environmental conditions, detect diseases, and optimize feeding strategies, hence improving animal welfare and operational efficiency. The integration of these advanced technologies bridges the gap between theoretical advancements and practical applications, shaping the future of sustainable farming practices [6].

Current Challenges in Traditional Farming

Traditional farming is facing some major challenges that prevent it from being efficient and sustainable. The most significant challenge is the dependency on natural weather conditions, making crop production vulnerable to climate change, erratic rainfall, and extreme weather events. Additionally, the problem of resource wastage, such as water and fertilizers, arises due to limited access to modern tools and techniques, which raises the cost and affects environmental sustainability. It lacks an efficient pest and disease management system in traditional farming. Therefore, yields are low, and more dependence is shown toward dangerous chemical pesticides. Small-scale farmers find more pressure from the lack of skilled labor and the high cost of hand interventions. Traditional farming is not able to fulfill the food requirements of people because of an increasing global population, and the need for increased productivity and resource utilization requires advanced technologies. So, address these challenges by bringing in modern approaches for farming to improve their strength with innovative solutions like automation, IoT, and machine learning [7].

The Role of Technology

Modern agriculture has faced the critical challenge of technology to pave the way for sustainable farming practices. It has advanced tools that enable the tracking and management of some of the critical parameters, such as soil health, crop growth, water usage, and pest control, in real-time using IoT devices, machine learning algorithms, and precision farming techniques. Drones and remote sensing help undertake efficient field surveys, and the analytics with the help of AI optimizes decision-making, based on the historical and real-time data available. Automation of irrigation, fertilization, and harvesting reduces dependence on labor forces and increases the productivity in particular resource-constrained settings. With cloud computing and blockchain, traceability is made better, ensuring less food waste. These technological innovations enhance agriculture efficiency and resilience while maintaining sustainability. This will help meet the food requirements of the world while conserving natural resources and minimizing negative effects on the environment [7].

Scope and Objectives

The scope of incorporating technology in agriculture encompasses the rectification of inefficiencies in conventional farming practices, improving productivity, and sustainability to meet the increased demands for food around the world. It involves the use of modern technologies such as IoT, machine learning, automation, and precision agriculture to optimize resource use, monitor environmental conditions, and enhance crop management practices. The focus should be on developing a climatic resilient agriculture system that would respond to variability in climatic conditions and deal with water deficiency, labor deficit, and pests infestation as well. That is crucial to the development of a sustainable paradigm of agriculture as a basis of food security and environmental conservation [8].

This will also help reduce the wastage of water, fertilizer, and energy in agriculture to provide better resource use efficiency. Productivity of crops can be enhanced by using data-driven decisions and automation. This technology also helps in bringing sustainable usage of chemicals with soil health, along with green practices. Real-time IoT monitoring and control systems allow key parameters to be observed continuously in a timely fashion so that there can be early intervention. Machine learning-based predictive analytics provides the knowledge of the crop health status, infestation with pests, and the implications of weather effects. Integration into such cost-effective, user-friendly tools is attempting to empower the small-scale farmer by transforming agriculture to become sustainable and inclusive for the sector as well [9].

LITERATURE SURVEY

Akbar et al. [10] presented an in-depth survey of deep learning-based computer vision techniques specifically engineered for greenhouse environment. The authors have discussed multiple applications, from crop growth monitoring to disease identification, yield evaluation, and quality assessment. Through the analysis of more than 100 studies, the authors identified key challenges, including scarcity of labeled datasets, limitations in terms of computational resources, and variations in greenhouse conditions across different regions. They also mentioned the need for domain-specific adaptations of deep learning techniques to be used in environments like greenhouses, which feature controlled lighting and temperature. To overcome the aforementioned limitations, the authors proposed future work, where multi-modal sensor fusion is used. In other words, they combined data coming from various sensors such as RGB (red, green, blue) cameras, thermal sensors, and hyperspectral imaging. Another recommendation made was developing deep learning models specifically for greenhouses to make them more efficient and sustainable. It also emphasized real-time data processing with edge computing to reduce latency and dependency on cloud infrastructures.

Farooq et al. [11] published an extensive review covering IoT technologies applicable in greenhouse agriculture, encompassing enabling technologies, applications, and communication protocols. The authors wrote about utilizing the potential of sensors, cloud computing, and automation to minimize use of the important resources – water, energy, fertilizers – as far as crop production and its yield and quality. The authors presented various IoT frameworks, such as long-range wide area network (LoRaWAN), ZigBee, and narrowband IoT (NB-IoT), and explained the relevance of those frameworks to applications in greenhouses. The authors also emphasized that strong security protocols are required for data and infrastructure protection against cyber threats. In addition, they presented AI and machine learning integration with predictive analytics as a future direction that would be critical. Such integration would be able to support tasks such as early disease detection, climate control optimization, and yield forecasting, filling the existing technological gaps. The study also pushed for an easy-to-use IoT platform that would readily be adopted by greenhouse operators, who may or may not be technically competent, hence promoting an even spread of the adoption of IoT-led intelligent agriculture solutions.

Su et al. in 2022 [12] had made an introduction of SE-YOLOv3-MobileNetV1 network specifically designed for the classification of tomato maturity in the natural greenhouse environment. The model effectively combined the basic structure of MobileNetV1 with the powerful extraction capability of features by SE-YOLOv3, optimizing this within devices and usually employed within resource-constrained devices typically utilized within agricultural deployment. It would yield considerable accuracy in detecting maturity levels of tomato in different environmental conditions like the variation of lighting, temperature, and humidity. This work demonstrated the practical applicability of deep learning in precision agriculture, providing a scalable solution for real-time monitoring and harvest planning. The authors also highlighted the possibility of integrating their model with IoT frameworks to enable automated decision-making in smart greenhouses.

Chen et al. [13] proposed a deep learning model for the accurate detection of greenhouse cucumber canopy vine structures. It is seen that the authors have combined coordinate attention mechanisms that could allow the model to better focus its attention on spatial features and suppresses the background noise. Sophisticated loss functions, which are designed specifically for object detection in cluttered environment, can be added to enhance the model's accuracy. This study has been conducted to emphasize the crucial role that plant architecture plays in optimizing greenhouse operations, including pruning, pollination, and yield estimation. This research applied cutting-edge AI techniques in order to provide a foundation for future innovations of automated greenhouse systems concerning the special challenges of crop management in greenhouse conditions.

Cong et al. [14] presented an advanced mask RCNN (region-based convolutional neural network) framework applied for the sweet pepper grown inside greenhouses with detection and segmentation. Their model overcame some complicated problems of occlusion because of overlapping leaves and fruits along with variable light conditions characteristic for controlled agricultural environment. With this improvement of mask RCNN, based on adaptive feature extraction and segmentation approaches, the performance turned out to be quite robust regarding the precise identification and classification of sweet peppers at all different growth stages. In so doing, the present study demonstrated that the adaptive computer vision models are relevantly applicable in depicting the dynamic, heterogeneous nature of the greenhouse environment. The authors proposed their model be integrated into robotic systems for automated harvesting and sorting that could lead to breakthroughs in precision horticulture.

Shinoda et al. published in 2023 [15] "RoseTracker," a novel greenhouse system, for the automatic monitoring of rose growth. It used object detection algorithms and image analysis techniques to track accurately the bud development, stem elongation, and leaf health. In this manner, the automation processes in "RoseTracker" significantly reduced dependency on labor-intensive manual labor that was often prone to human errors. The system ensured real-time collection, and the growers were able to garner workable know-how on achieving ideal irrigation application, nutrient intake, and controlled climatic use. Of course, these results underscore "RoseTracker" flexibility over very wide ranges of greenhouse conditions – changed lighting, temperatures, among others. The authors noted that this innovation could be combined with IoT-based smart agriculture systems, where the data collected by the system would be analyzed through machine learning models to provide predictive insights. This innovation demonstrated how automation and advanced analytics could enhance the efficiency, sustainability, and profitability of greenhouses, thus making it a very important tool for modern horticulture. The study further sets the basis for the extension of similar technologies to other high-value crops, promoting further research on crop-specific automated monitoring solutions.

Verma et al. [16] have designed a prediction system that is machine learning-based with optimal uptake of nutrients for increased growth in hydroponic farming. Tomatoes are cultivated using nutrient film technique wherein the soil-less cultivation is carried out, and parameters considered include composition of Normal saline (NS), ion concentration (Na, K, Mg, N, Ca), dry weight matter, and electrical conductivity (EC). Given by machine learning algorithms, the system forecasts absolute crop growth rate so precision adjustments of hydroponic set up are achievable. The authors particularly mentioned that with specific ion monitoring, even traditional EC controls can be overcome to ensure maximum uptake of nutrient. Potassium (K) ions were the most critical for uptake; however, the reverse trend was noted for calcium (Ca) ions, as it was the least uptake and highest, indicating that there may be some change within the nutrient solutions. The above approach will guarantee high yield, reduce the nutrient wastage, and will be able to throw light on nutrient uptake dynamics over different growth stages. This framework shows that AI-driven solutions have potential to enhance the efficiency and scalability of hydroponic systems. Moreover, it is also underlining the importance of advanced technologies coupled with sustainable agriculture practices in view of the challenge posed by global food security issues.

Kondaka et al. [17] proposed a smart hydroponic farming system that integrated the use of machine learning and IoT for efficient management of crop growth. The designed system used deep water culture (DWC) and nutrient film technique (NFT) in a hybrid manner to tap the advantages offered by both the methodologies while consuming least energy. The parameters include EC, water temperature, and humidity. All these parameters are controlled with sensors DHT11 and DS18B20 running with the aid of a Raspberry Pi. The machine learning module takes advantage of random forest regression to predict the nutrient consumption needs of crops in changing environmental conditions with an accuracy of 92.87%. A web application helps users to engage with the system, select crops, and monitor growth. As stated above, the automated system does enhance the dose of nutrients and water, allowing for higher yields than traditional farm methods of using water. There is a publication here where the scientist speaks about how IoT combined with machine learning formulates sustainable urban-friendly hydroponics.

Patil et al. [18] designed an AI-based hydroponic system for the cultivation of lemon basil using the DWC method. The system utilizes IoT and AI to monitor and control the key environmental parameters such as pH, EC, humidity, and temperature. Sensors like DHT11, pH, and EC sensors collect real-time data, which is processed using a Raspberry Pi and Arduino-based architecture. The Open Agriculture

Initiative dataset has been used to build prediction models for plant height using the algorithms of linear regression, lasso regression, multilayer perceptron (MLP), and random forest regressor. Out of the four models, the highest prediction accuracy of 79% was recorded in the MLP model. The system utilizes an open-source software called Hydrobuddy for the preparation of optimized nutrient solutions for the growth of plants. A growth model that was utilized here is called Richard's growth model, which has been simulated as a means to verify the actual biological plant growth over time. This new approach shows how with AI and IoT in hydroponics, the productivity of the crops may increase and the waste of resources is minimized. This study discusses the use of automated systems for controlled environment agriculture, particularly in the urban context, as a mitigation strategy against the global food security issues.

Arora et al. [19] developed an automated dosing system for hydroponics based on the IoT and machine learning for nutrient delivery optimization. The system relies on the NFT and involves sensors that track environmental parameters, such as pH, EC, temperature, and humidity. Data is acquired and processed by an Arduino UNO using artificial neural network (ANN) to control dosing and maintain appropriate growing conditions through the analysis by artificial neural networks. A backpropagation-based ANN model has been utilized, comprising an input layer, a hidden layer, and an output layer to predict the nutrient and water requirements in terms of environmental conditions with high precision as maintained with respect to ideal pH and EC levels. Real-time monitoring and control have been ensured by integration of IoT into this web application to reduce human interference for proper utilization of resources. The system shows the possibility of using IoT and machine learning for sustainable agriculture, providing a scalable solution for urban farming and solving the problem of limited arable land. Limitations that researchers identified in this system include vulnerability to power outages and increased electricity consumption as compared to traditional systems, which will be an area for improvement in the future to enhance efficiency and resilience.

Malarvizhi et al. [20] developed an integrated smart farming system which is monitored and controlled based on IoT and artificial intelligence–machine learning (AI-ML) techniques for hydroponic farming. The suggested system uses sensors, including pH, temperature, ultrasonic, and CO_2 enabled through IoT with sensor readings given live to a dashboard with actionable insights in the plant's growth condition. The system, for disease detection, uses augmented datasets trained on convolutional neural networks (CNNs) and achieves a validation accuracy of 96.7%. The CNN model uses RGB data to classify plant diseases considering features such as color, texture, and shape. The system also makes use of cloud integration via Adafruit to enhance remote monitoring, thus improving the operational efficiency of the system. This study highlights the potential use of IoT in conjunction with AI-ML for the optimization of agricultural practices with less human interference, high quality of yields, and sustainable farming. Improvements would be future-oriented in that it could expand to cover multiple crop types and various environmental conditions.

Friha et al. [21] presented the most exhaustive overview of emerging technologies for smart agriculture based on IoT including an in-depth classification of seven categories of application: smart monitoring, water management, agrochemical applications, disease management, harvesting, supply chain management, and agricultural practices. The publication also reviewed such enabling technologies like unmanned aerial vehicles (UAVs), wireless communication protocols, blockchain, fog computing, and middleware platforms. Some of the notations include describing a taxonomy for blockchain technologies designed for supply chain management in agricultural, case study illustrating how it has been incorporated into practice under agriculture, and including open challenges-interoperability and scalability, which pose energy consumption efficiency and have barriers to a development cost into agricultural IoT application. The reports detailed the description of interoperability, scalability, energy efficiency and cost barriers developed into agricultural applications of IoT. This survey is useful for both researchers and practitioners, as it gives a panoramic view of how IoT can help improve agricultural productivity and sustainability.

Liu and Jiang [22] introduced an AI-based NeuroAqua system to optimize the efficiency and stability of aquaponics systems. It uses a combination of IoT and machine learning that will take advantage of the data being fed to it by the wireless sensors in monitoring environmental conditions, water quality, and nutrient level. The structured data is inputted into the database for evaluation. Using XGBoost, random forest, and ANN to predict the plant growth. Here, it has shown XGBoost resulted in 91.6% accuracy. This work incorporated computer vision using OpenCV, where a series of processes involved automated measurements to prevent human errors due to hand measurements. Feature importance analysis revealed nitrogen, nitrate, and nitrite as the most important factors affecting plant growth, besides light and phosphorus. This study will demonstrate the potential of AI-based aquaponics systems to maximize resource utilization, reduce labor inputs, and provide actionable recommendations for the system to improve further. Future work will be the development of a dataset of multiple crops and types of fish, which will make better predictions and achieve higher scalability.

An IoT and AI-based aquaponics system developed for optimization in terms of farming efficiency. Jiang and Liu [23] included integration of six diverse types of sensors that are installed to measure parameters like environmental or water, in the system- air temperature, humidity, pH, nitrogen, phosphorus, potassium, light intensity, will be sent towards a cloud database designed especially for structured data of ML analysis. The system was tested for performance in both a lab and in a large commercial farm called Ouroboros Farms. Predictions of important factors of plant growth were made with the help of machine learning algorithms, such as XGBoost, random forest, and neural networks. Out of all of them, XGBoost delivered the highest at 91.6% accuracy. The computer vision module uses OpenCV for monitoring the plants' growth with the help of image processing. It also provides real-time monitoring with web-based alerts whenever parameters go out of their ideal range. The proof-of-concept study shows that AI-based aquaponic systems are not just viable but also decrease the intensity of labor, increase the resource usage, and improve crop productivity. Future work will comprise scaling the system up to support various crops and environments to further refine the machine learning models.

Nguyen et al. [24] presented a machine learning-based system for estimating and predicting the nitrite concentration in aquaculture water. The proposed "NO_2 Assistant" system would automatically monitor water quality through an integration of IoT devices and ML models. The main controlling device is a Raspberry Pi 3, which contains peripheral devices like a camera, servo motors, water pump, and dispenser of reagent used in the collection and processing of water samples. The system evaluates the color of the liquid solutions, which is an indication of nitrite levels in the water through image processing techniques. The supervised machine learning algorithms to design five categories from the classification levels of nitrites are good, tolerable, harmful, dangerous, and toxic; in such experiments, results obtained with 95% using ANN in a testing phase but it is trained up to only 94%. Automatic and manual modes of transmission for the information gathered from the IoT to be communicated to a mobile application-based system that further performs remote monitoring and warning service. This innovative approach shows the prospect of AI-based solutions in the aquaculture sector for quality water monitoring with less manual efforts and increased productivity. Future improvements include building up the data set for enhanced generalization ability and environmental variability consistency for perfect performance.

Singhal et al. [25] have elaborated on the installation of AI and ML in aquaculture for the key challenges such as environmental monitoring, disease detection, feed optimization, and stock assessment. The paper articulates how IoT, satellite surveillance, and ML can provide real-time aquaculture insights into the precise and efficient management of aquaculture practices. Key applications involve ML-based image analysis in diagnosing fish disease, optimizing fish feed with the help of ANN models, and predictive analytics on sustainable fishery management. The use of AI-powered systems was essential to develop it and then get integrated with fish farms to decrease reliance on labor as much as decision making could improve. Data-related inconsistencies and socio-economic issues about sensor faults for adoption are reported issues. Recommendations include making low-cost and rugged sensing technology available and increased interdisciplinary collaboration from experts toward achievement of sustainable aquaculture solution.

Venkatraman and Surendran [26] introduced an Industry 5.0 aquaponics system with optimized farming by machine learning and IoT technologies. It incorporates sophisticated sensor networks and IoT devices for real-time monitoring of environmental parameters, such as pH, temperature, dissolved oxygen, and nutrient levels. The advanced machine learning models, support vector machine (SVM), and neural networks are applied to predict the time of maintenance, optimize the usage of resources, and adjust it in real time to achieve improved efficiency. The system uses an innovative approach of automation and robotics for operational tasks like feeding fish, water circulation, and monitoring plant growth. It promotes sustainable farming, minimizes water wastage, optimizes resource usage, and provides precise control over farming conditions. A cloud-based platform is used to monitor the farm from a distance and analyze data to give farmers actionable insights for better decision-making. This research underlines the prospect of Industry 5.0 synergy with aquaponics to promote a future in agriculture where problems about scalability, resource efficiency, and environmental sustainability may be addressed.

Arvind et al. [27] in the year 2020, proposed an edge computing-based smart aquaponics monitoring system that utilized IoT and deep learning algorithms for optimizing plant and fish growth. The above system used sensors like DHT11 for temperature and humidity, BH1750 for light intensity, HC-SR04 for water level, soil moisture sensors, and pH sensors. Data from these sensors is processed at the edge using a Raspberry Pi, and thus real-time monitoring and control is achieved. The authors utilized the TPOT AutoML library for automatic machine learning model selection on tasks of triggering events like control of UV lights, water pumps, and fans. The algorithm for instance segmentation with deep learning mask R-CNN was applied to the fish detection and counting. It was highly efficient, showing a mean average precision (mAP) of 75% and an F1-score of 95.56%. It also greatly improved the water quality through maintaining optimal pH levels and lessened water consumption compared to traditional methods. The paper emphasizes the possibility of IoT, edge computing, and deep learning integration in aquaponics to advance efficiency, decrease labor work, and facilitate sustainable farming. The potential future work is developing federated learning models for large-scale deployments to enhance scalability as well as data privacy.

Wang et al. (2020) [28] designed an aquaponics system as a practical teaching tool for the education of students on computational intelligence techniques. It is an aquaculture-hydroponic symbiotic system, which employs PLC (programmable logic controller) and LabVIEW for data acquisition, monitoring, and control. It provides real-time monitoring of parameters such as pH, dissolved oxygen, and conductivity, which are necessary for the regulation of ammonia and nitrite nitrogen levels critical to both plant and fish growth. The teaching approach used was project-based learning, in which the students were able to examine computational intelligence ideas, including soft measurement models. Techniques were multiple linear regression (MLR), partial least squares (PLS) and support vector regression (SVR), and there were neural networks applied for predictive modeling. The study emphasizes further that although a nonlinear model is insisted to be usable with data sets even with small amounts, SVR in particular could be an efficient data determination with high precision. This innovation points the problem into the gap between theoretical knowledge and applying it into reality, which enhances practical capabilities and increases understanding among students concerning the intelligent systems applied. Future extension will include enhancement of the data set and more parameters of water quality for sophisticated studies.

Li et al. [29] proposed a framework for the automated detection of poultry farms from high-resolution aerial images to address biosecurity risks and unregulated farming practices. The study made use of ML and computer vision techniques to process geospatial data and estimate farm capacity. The authors, by using remote sensing datasets and advanced object detection networks such as ReDet, were able to identify poultry farm locations and estimate their capacities through the measurement of barn areas.

The system integrates geospatial layers such as road networks and watersheds into a biosecurity knowledge base that improves actionable decision-making for disease prevention and resource allocation. These also include the duality of designs for farm location and capacity measurement, which shows high accuracy – the mAP for farm location is 87.5%. This implies that effective managing and regulating animal farms can eliminate public health problems and inform on agricultural policies; the authors' suggestion is using the framework by adapting it with other types and the larger geographical boundaries in future for scalability and applicability.

Ali et al. [30] designed an intelligent control shed poultry farm (CSPF) system combining IoT and ML for automation in environmental monitoring and control. Sensors deployed in the system include DHT11 for temperature and humidity, MQ135 for gas detection, light-dependent resistor (LDR) for light intensity, and water level sensors. These sensors feed information to a Raspberry Pi 3B+ board, where this information is analyzed and, using actuators in the form of fans, heaters, lights, and water pumps, controls its own environment. It used five models of machine learning: decision tree (DT), random forest (RF), K-nearest neighbor (KNN), SVM, and naïve Bayes (NB) for autonomous decision-making. Out of the applied models, the DT model could have an accuracy rate of up to 99.97% which allowed an effective regulation based on historical data. The system will be scalable, and adaptable in poultry farm sizes and breeds and hence promote effective use of available resources and diminish labor dependency. Future directions may include wireless sensors integration, advancement of data security, and developing a mobile application for the purpose of monitoring and control through remote access. This research illustrates the potential use of AI-based solutions in modernizing poultry farming towards sustainable efficient operations.

Feraldi and Enriko (2022) [31] proposed a model using machine learning that could facilitate an automatic approach toward temperature and humidity control for smart poultry farms. In the work, they employed the KNN algorithm to find out the precise speed of fan as a basis to regulate conditions and reduce stress through heat by promoting the efficiency of broiler chickens. Their data set is of 210 records with parameters on temperature, humidity, and the fan's speed. A system with two classes of output classes, 10 iterations, and a k-value of 3 obtained a maximum accuracy of 97.36%. The integration of sensors would allow for monitoring and control on real-time using the proposed automation through microcontroller-based systems. Cross-fold validation further validated performance by achieving a mean accuracy of 96.60% and two outputs, though accuracy began to decrease at higher output classes. This indicated that there could be problems when using KNN for multi-class prediction. It is clear from this research that AI and ML can assist in optimizing the operations of a poultry farm, reduce manual intervention, and increase sustainability. Future work includes increasing the dataset and researching advanced algorithms for improving accuracy at higher output classes.

SYSTEMATIC REVIEW

This section provides a systematic review of the relevant literature on IoT and AI-driven integrated farming systems based on hydroponics, aquaponics, and poultry farming. All these systems have been integrated to get maximum efficiency concerning resources, automation, and sustainability through AI and IoT. Table 1 provides details on the methodology of each study, its technological approach, and its findings.

RESEARCH GAP

In the meantime, there remain significant gaps that limit their overall potential to alleviate global agricultural challenges. For one, the use of AI, IoT, and ML suffers from the deficiency of large, high-quality, and labeled datasets developed for different types of environmental and crop conditions. The current availability of datasets for agricultural purposes remains inadequate to accommodate the heterogeneity of practices associated with regions; thus, such AI models become unsuitable for being generalized across most regions. This gap is most noticeable in large-scale farming situations, where models trained in a controlled environment like greenhouses start to perform worse in open-field conditions with uncontrolled variables.

Table 1. Systematic review.

S.N.	Author(s)	Title of the Project	Methodology	Technical Aspect	Overview
1	J. U. M. Akbar et al. [10]	Deep Learning Assisted Computer Vision Techniques for Smart Greenhouse Agriculture	Review of deep learning techniques for greenhouse environments.	Focus on domain-specific models for greenhouses.	Proposes greenhouse-specific deep learning models.
2	M. S. Farooq et al. [11]	Internet of Things in Greenhouse Agriculture: A Survey	Survey on IoT technologies optimizing resources and improving crop quality.	Integration of IoT frameworks and predictive analytics.	Examines IoT integration for smart agriculture.
3	F. Su et al. [12]	Tomato Maturity Classification Using SE-YOLOv3-MobileNetV1 Network	Combines MobileNetV1 with SE-YOLOv3 for tomato classification.	Optimized for resource-constrained devices.	Real-time monitoring and harvest planning.
4	M. Chen et al. [13]	Intelligent Recognition of Greenhouse Cucumber Canopy Vine Top	Coordinate attention for enhanced spatial feature detection.	Tailored loss functions for cluttered environments.	Focus on greenhouse cucumber canopy analysis.
5	P. Cong et al. [14]	Instance Segmentation Algorithm for Greenhouse Sweet Pepper Detection	Adaptive feature extraction for segmentation with mask RCNN.	Addresses occlusion and variable lighting conditions.	Automated pepper harvesting and sorting.
6	R. Shinoda et al. [15]	RoseTracker: Automated Rose Growth Monitoring	Object detection algorithms for rose growth metrics.	Automates growth monitoring metrics.	Significant labor reduction in rose growth monitoring.
7	Swapnil Verma et al. [16]	ML-based Prediction System for Nutrient Uptake in Hydroponics	Prediction of nutrient uptake using machine learning.	Optimizes hydroponic nutrient solutions.	Enhances hydroponic system efficiency.
8	Lakshmi Sudha Kondaka et al. [17]	Smart Hydroponic Farming System with ML	Combines IoT with ML for crop growth management.	Sensor monitoring for real-time adjustments.	Low-maintenance hydroponic farming system.
9	Shreya P. Patil et al. [18]	AI-Driven Hydroponic System for Lemon Basil	AI integration for hydroponic farming control and prediction.	Accurate plant height prediction using ML models.	Improved crop productivity with resource optimization.
10	Utkarsh Arora et al. [19]	Automated Dosing System in Hydroponics Using ML	Automated nutrient dosing using IoT and ANN models.	Real-time nutrient adjustments based on environmental data.	Scalable automation for hydroponics.
11	Malarvizhi P. et al. [20]	Integrated Smart Farming Technique Using IoT and AI-ML	IoT sensors with CNN for smart farming and disease detection.	IoT-enabled real-time disease detection.	Optimized agricultural resource use and quality yield.
12	Othmane Friha et al. [21]	IoT for the Future of Smart Agriculture: Comprehensive Survey	Comprehensive review of IoT applications and technologies.	Emerging technologies in IoT-based smart agriculture.	Recommendations for future IoT innovations.
13	Jayden Liu and William Jiang [22]	Optimization of Aquaponics System Using AI Approach	Integration of AI in aquaponics for resource optimization.	AI for predictive plant and fish growth management.	Improves aquaponics system efficiency.
14	William Jiang and Jayden Liu [23]	NeuroAqua: AI and IoT-Based Aquaponics System	IoT-based aquaponics system using ML algorithms.	IoT and ML for aquaponics automation.	Actionable insights for farming conditions.

15	Nhan Nguyen et al. [24]	ML for Assessment and Prediction of Nitrite in Aquaculture Water	Nitrite prediction using IoT and ML models.	Automated nitrite level classification.	Enhances water quality monitoring in aquaculture.
16	Amit Singhal et al. [25]	Emerging Technologies in Fish Farming with AI	AI and ML for environmental monitoring and decision-making.	AI for disease detection and resource management.	Innovations for sustainable aquaculture.
17	Venkatraman M. and Surendran R. [26]	Industry 5.0 Aquaponics System Using ML	IoT and ML-based Industry 5.0 aquaponics system.	IoT-based aquaponics with predictive maintenance.	Real-time aquaponics management for efficiency.
18	Arvind C. S. et al. [27]	Edge Computing in Smart Aquaponics Monitoring	Edge computing and deep learning in aquaponics.	Edge computing for aquaponics monitoring.	Deep learning to optimize aquaponics systems.
19	Wei Wang et al. [28]	Aquaponics System Design for Computational Intelligence Teaching	Aquaponics system for computational intelligence education.	Educates on intelligent system implementation.	Real-world application in intelligent farming.
20	Yu Li et al. [29]	Automated Detection of Poultry Farms from Aerial Images	Aerial image analysis for poultry farm detection.	AI for farm localization and capacity estimation.	AI for improved poultry farm biosecurity.
21	Muhammad Ali et al. [30]	Intelligent Control Shed Poultry Farm System	IoT and ML for automated poultry farm management.	Automated control of environmental conditions.	Efficient resource management in poultry farming.
22	Rahmantio Feraldi and Enriko IK [31]	ML Model for Temperature and Humidity Control in Poultry Farming	ML-based temperature and humidity control in poultry farms.	Optimizes environmental controls using KNN.	Enhances poultry farming sustainability.

Scalability and accessibility also become critical issues. Although the AI-driven and IoT-enabled systems have much potential, their very high deployment and maintenance costs mean that they are out of reach of small-scale and resource-poor farmers. Furthermore, user-friendly interfaces and localized solutions designed for low-tech users exacerbate the problem. Integration challenges also persist, as many systems struggle to seamlessly combine IoT sensors, machine learning algorithms, and cloud computing platforms. Interoperability among devices and platforms often leads to fragmented data systems, reducing the efficiency and impact of these solutions.

Another challenge relates to energy and resource efficiency. Most applications and systems use cloud-based infrastructure for computing, which further increases energy usage and latency. Edge computing and low-power solutions have great benefits, but there are limitations, both technically and financially, behind their adoption. Real-time decision-making capabilities for critical applications like disease detection or irrigation control also are often weak. Delays in processing and executing actions severely limit the effectiveness of these automated interventions, especially in time-sensitive scenarios.

Other significant barriers include existing models not possessing domain-specific customization. The performance is suboptimal in the current systems because they do not take into account particular crop, climate, or type of farming, among others. Adaptable models will be needed for them to fit local agricultural contexts for these needs. Data security and privacy are also concerns since agriculture is becoming more data-driven. Very lax cybersecurity measures around these systems thus expose them to potential threats against reliability and adoption.

Emerging technologies include advanced AI models, IoT, and edge computing. Domain-specific AI and machine learning models, like transfer and federated learning, negate the limitation associated with data while maintaining the privacy of information. The deployment of IoT-enabled sensors along with interoperable platforms such as LoRaWAN and ZigBee improves real-time monitoring and decision-making, along with the support of edge computing for low-latency processing. Automation and robotics including drones and adaptive robots optimize labor-intensive tasks. Blockchain ensures that any type of data management is secure and transparent, while multi-modal sensor fusion enhances crop health and disease detection accuracy. Hybrid cloud-edge systems are beneficial as they provide scalability along with responsiveness. Open-source platforms that combine training programs enable technologies to be used by small-scale farmers. Sustainability is further guaranteed through the use of solar-powered devices. The innovations supplement each other to transform agriculture into a more efficient, resilient, and inclusive sector. It requires the concerted efforts of AI researchers, agricultural experts, and policymakers to bridge these gaps. Addressing these challenges can lead to future advancements that pave the way for innovative, scalable, and inclusive solutions transforming agriculture into a sustainable and efficient domain.

DISCUSSION

Advanced technologies such as AI, IoT, and robotics could revolutionize traditional farming practices, addressing some of the most critical challenges that plague agriculture today, including resource inefficiency, labor dependency, and climate variability. AI predictive analytics can be used to predict issues such as pest infestations and crop diseases, while IoT sensors monitor environmental conditions in real time, ensuring timely interventions. Edge computing and automation not only speed up and increase the efficiency with which decisions can be made, such as particularly in non-delayed matters like water irrigation and fertilization, but robotics and drones reduce labor power requirements, enhancing scalability and efficiency.

While all these are welcome improvements, they remain challenging to scale up for the diverse agricultural environments, particularly for small-scale and resource-poor farmers. The implementation cost is too high, and the interfaces are not user-friendly; good-quality datasets are not easily available. Devices and platforms interoperability as well as data security pose a huge challenge. Again, specific crops and regions require special solutions and hence cannot be effectively implemented across all areas.

These technologies can be refined and expanded to suit filling any gap left by previously existing gaps by engaging in collaborative efforts among AI researchers, agricultural experts, and policymakers. The discussion goes on to explain the possibility of combining these innovations with sustainable practices for enhancing productivity and environmental conservation so as to ensure food security among a growing world population. Such challenges require efforts focused on the availability, affordability, and adaptability of technology to the diversified needs of agriculture.

CONCLUSION

In conclusion, through the integration of advanced technologies, such as AI, IoT, and robotics, agriculture has transformed, addressed inefficiencies, and limitations by traditional farming methods. These solutions help solve a few critical problems: resource optimization, climate adaptability, and scalability, that farmers can take to enhance their productivity, costs, and more importantly, towards sustainable practices. AI-powered predictive analytics, IoT-based real-time monitoring, and automation through robotics and drones have immense opportunities to increase operational efficiencies and better decision-making in different agricultural segments. Nevertheless, the adoption of these technologies presents many challenges. High costs, limited scalability, lack of interoperability, and data security issues are some of the restrictions that prevent widespread implementation of these technologies, especially among small-scale farmers. The development of domain-specific models, affordable solutions, and user-friendly interfaces is crucial to bridge these gaps and ensure inclusivity. Moreover, collaboration among researchers, policymakers, and agricultural stakeholders can accelerate innovation and make these technologies more accessible.

This role of technology in agriculture becomes crucial since the demand for food globally continues to increase. If the existing challenges are met through the use of AI, IoT, and the advancement of robotics, agriculture would be transformed into a more efficient, sustainable, and resilient sector that can respond to future demands with minimal environmental resources. In this regard, transformation is considered crucial for realizing global food security and economic as well as social well-being.

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