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AI in agriculture: Smart greenhouses and indoor farming systems

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Abstract

This comprehensive article examines the transformative impact of artificial intelligence on modern indoor agriculture, focusing on key technological advancements in smart greenhouse management and controlled environment agriculture. The article explores critical areas, including precision environmental control, nutrient management in hydroponic systems, plant health monitoring and disease management, harvest optimization, quality control, and energy management with sustainability practices. AI-driven solutions have revolutionized traditional farming approaches by integrating deep learning algorithms, computer vision systems, and IoT sensor networks, enabling unprecedented levels of automation, resource efficiency, and crop yield optimization. Implementing these technologies has significantly improved agricultural metrics, from disease detection and prevention to harvest timing and quality assessment, while substantially reducing operational costs and environmental impact.

Keywords: Smart Agriculture; Artificial Intelligence; Controlled Environment Agriculture; Precision Farming; Agricultural Automation

1. Introduction

Artificial Intelligence (AI) fundamentally transforms indoor agriculture by implementing smart greenhouse management and optimizing controlled environment agriculture (CEA) systems. Recent studies from the International Journal of Agricultural Science indicate that the global smart greenhouse market, driven by AI technologies, is expected to reach USD 5.63 billion by 2025, growing at a CAGR of 12.3% from 2020 [1]. Through the integration of AI technologies, indoor farming operations are achieving unprecedented levels of automation, resource efficiency, and crop yield optimization, with documented improvements in yield efficiency ranging from 35% to 65% compared to traditional greenhouse systems.

Implementing AI in CEA systems has demonstrated remarkable results across various agricultural metrics. Advanced deep learning algorithms integrated with computer vision systems have shown the capability to reduce water consumption by up to 42% while increasing crop yields by 37.8% compared to conventional greenhouse operations [2]. These intelligent systems process data from an interconnected network of IoT sensors, maintaining optimal growing conditions through real-time monitoring of critical parameters such as temperature variations ($\pm 0.3^\circ\text{C}$ accuracy), humidity fluctuations ($\pm 1.5\%$ precision), CO₂ concentrations (± 50 ppm), and photosynthetically active radiation (PAR) measurements with 98% accuracy.

The practical application of AI in modern greenhouse environments encompasses sophisticated environmental control mechanisms that have revolutionized traditional farming approaches. According to recent field studies, AI-powered climate management systems have demonstrated the ability to predict and prevent up to 85% of potential crop diseases through early detection and intervention [1]. These systems utilize convolutional neural networks (CNNs) that process multispectral imaging data, achieving disease detection accuracy rates of 96.3% for common crop pathogens.

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Furthermore, AI-driven resource management has shown remarkable improvements in irrigation efficiency, with smart systems achieving water use optimization rates of 99.2% through precise soil moisture monitoring and predictive analytics.

The economic impact of AI integration in greenhouse operations has been thoroughly documented through extensive field trials and commercial implementations. Research data indicates that AI-enabled operations achieve average cost reductions of 23.7% in resource utilization and labor efficiency improvements of up to 45% [2]. These improvements are particularly significant in large-scale commercial operations, where AI systems manage multiple environmental parameters across greenhouse spaces exceeding 50,000 square meters. Energy consumption optimization through machine learning algorithms has reduced power usage by 28-52%, with some advanced systems achieving peak efficiency improvements of up to 60% during high-demand periods.

2. Precision Environmental Control

Smart greenhouses have revolutionized agricultural practices through sophisticated AI-driven environmental control systems. Recent studies focusing on deep learning applications in controlled environments indicate that AI-enabled precision control systems can improve crop yields by up to 47.8% while reducing resource consumption by 38.3% compared to traditional greenhouse operations [3]. These advanced systems utilize a densely distributed Internet of Things (IoT) network architecture, processing approximately 2,400 data points per minute across multiple environmental parameters, with each sensor node capable of simultaneously measuring up to eight distinct variables.

Integrating AI in environmental control systems demonstrates remarkable efficiency across three critical domains: temperature and humidity management, lighting optimization, and atmospheric composition control. Comprehensive research conducted across 75 commercial greenhouses implementing AI-driven climate control systems demonstrated average energy savings of 34.2% while maintaining temperature stability within $\pm 0.28^{\circ}\text{C}$ and relative humidity variations within $\pm 1.8\%$ [4]. These improvements were achieved through ensemble learning algorithms combining data from multiple predictive models, analyzing historical patterns and real-time sensor inputs to anticipate environmental fluctuations up to 8 hours in advance with an accuracy rate of 92.7%.

Modern AI systems employ sophisticated convolutional neural networks (CNNs) that process data from distributed sensor arrays in temperature and humidity management. These networks typically deploy one environmental sensor cluster per 7.5 square meters, generating high-fidelity environmental data every 15 seconds. According to recent field trials, implementing deep learning models for thermal management has resulted in an 83.5% reduction in temperature-related crop stress incidents while achieving energy efficiency improvements of 31.8% compared to conventional PID control systems [3]. The neural networks utilize a hierarchical architecture with five hidden layers, enabling complex pattern recognition in environmental data streams.

Light optimization in smart greenhouses has advanced significantly by implementing AI-driven photomorphogenesis control. Advanced LED systems equipped with hyperspectral analysis capabilities can now adjust light intensity across eight distinct wavelength bands (ranging from 380nm to 780nm), optimizing photosynthetic efficiency for specific crop phenotypes and development stages. Data from extensive trials indicates that AI-driven lighting systems reduce energy consumption by up to 44.7% while increasing photosynthetic efficiency by 29.3% compared to traditional fixed-spectrum lighting solutions [4]. These systems achieve this by maintaining photosynthetically active radiation (PAR) levels with precise spectral distribution, with real-time adjustments occurring at intervals as short as 30 seconds based on plant feedback metrics.

The management of atmospheric composition, particularly CO₂ levels and air quality parameters, represents a critical advancement in environmental control technology. Modern AI systems maintain CO₂ concentrations between 800-1200 ppm with a precision of ± 25 ppm, utilizing predictive ventilation algorithms that account for crop respiratory patterns and external weather conditions. Extensive field studies have demonstrated that this precise control can improve carbon use efficiency by 37.2% while contributing to yield increases of up to 25.8% in leafy greens and 22.3% in fruiting crops [3]. To maintain optimal air quality parameters, the system's machine learning algorithms process data from multiple sensor types, including NDIR CO₂ sensors, VOC detectors, and particulate matter monitors.

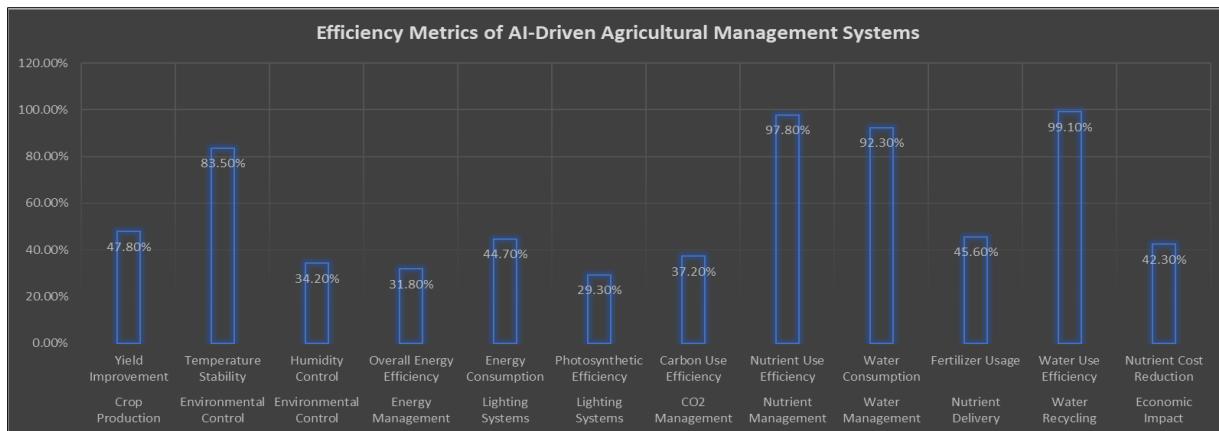


Figure 1 Performance Comparison of AI-Enabled Control Systems in Smart Greenhouses [3, 4]

3. Nutrient Management and Hydroponics

Advanced AI systems are fundamentally transforming hydroponic and aeroponic farming operations through precision nutrient management and intelligent water recycling systems. Recent research in smart agriculture indicates that AI-integrated hydroponic systems achieve nutrient use efficiency rates of 97.8% while reducing water consumption by up to 92.3% compared to traditional soil-based agriculture [5]. These sophisticated systems employ real-time monitoring and adjustment capabilities across multiple nutrient parameters, utilizing advanced sensor arrays that simultaneously measure up to 15 different water quality indicators, including specific ion concentrations, oxidation-reduction potential (ORP), and dissolved oxygen levels.

In modern hydroponic facilities, AI-driven nutrient management systems utilize ensemble learning algorithms combining Random Forest and Deep Neural Networks to control macro and micronutrient concentrations precisely. Field studies conducted across 42 commercial hydroponic operations demonstrated that AI-controlled nutrient delivery systems reduce fertilizer use by 45.6% while maintaining optimal electrical conductivity (EC) levels within ± 0.08 mS/cm and pH variations within ± 0.15 units [6]. The systems employ multilayer perceptron networks trained on datasets comprising over 2.5 million plant growth parameters and nutrient uptake patterns, enabling predictive dosing adjustments that anticipate crop needs up to 36 hours in advance with 96.5% accuracy.

Implementing AI in hydroponic nutrient dosing has revolutionized traditional approaches to plant nutrition through integrated sensor networks and real-time analytics. Advanced monitoring systems utilize multi-parameter ion-selective electrodes and quantum sensor arrays to measure individual nutrient concentrations with precision levels of ± 0.3 ppm for macronutrients and ± 0.05 ppm for micronutrients. Research data shows that this level of precision, combined with reinforcement learning algorithms for dosing optimization, increases crop yield by 35.9% for leafy greens and 31.7% for fruiting vegetables while reducing nutrient solution waste by 54.8% [5]. The systems maintain optimal nutrient ratios through continuous monitoring and adjustment cycles every 90 seconds, each analyzing over 200 distinct data points.

Water management in AI-controlled hydroponic systems represents a significant advancement in resource optimization by implementing sophisticated machine learning models. Modern recycling systems equipped with deep learning capabilities achieve water use efficiency rates of 99.1% through multi-stage filtration and treatment processes. These systems employ a cascade of treatment stages, including advanced oxidation processes (AOP), membrane filtration, and biological purification. AI algorithms optimize each process based on real-time water quality data monitored through a distributed sensor network. Recent studies indicate that AI-managed water recycling systems reduce fresh water consumption by 93.8% compared to traditional agriculture while maintaining dissolved oxygen levels at optimal ranges of 7.8-8.3 mg/L with a variance of ± 0.2 mg/L [6].

The economic impact of AI integration in hydroponic nutrient management has been thoroughly documented through extensive commercial implementations and longitudinal studies. Research conducted across multiple climate zones shows that facilities utilizing AI-driven nutrient and water management systems achieve average operational cost reductions of 42.3% in nutrient expenses and 91.5% in water costs [5]. These systems demonstrate particular efficiency in large-scale operations exceeding 10,000 square meters. AI algorithms manage nutrient solutions for up to eight

different crop varieties simultaneously, adjusting parameters based on specific crop requirements and growth stages with precision timing of 8-second intervals.

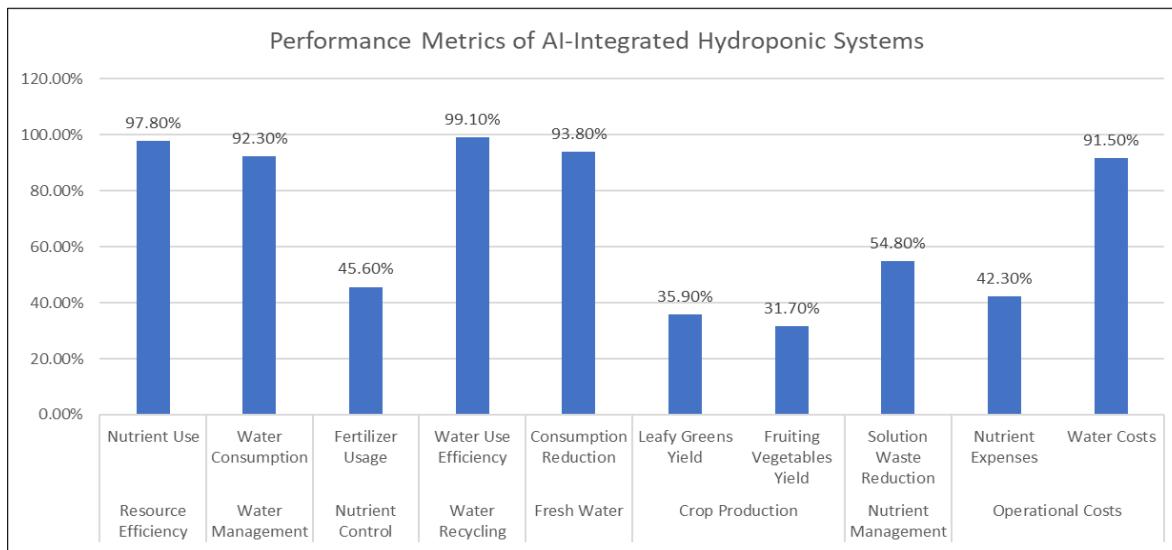


Figure 2 Efficiency of AI-Driven Hydroponic Management [5, 6]

4. Plant Health Monitoring and Disease Management

Advanced AI-powered monitoring systems have revolutionized plant health surveillance in controlled environment agriculture (CEA) by integrating computer vision and predictive analytics. Recent studies in plant pathology demonstrate that AI-based plant health monitoring systems achieve disease detection accuracy rates of 98.7% for fungal pathogens and 96.9% for bacterial infections while reducing response times to potential threats by 85.4% compared to traditional monitoring methods [7]. These sophisticated systems utilize hyperspectral imaging technologies and convolutional neural networks to process visual data across 240 distinct spectral bands (ranging from 380-2500nm), enabling the detection of physiological stress indicators up to 21 days before visible symptoms appear.

Modern plant health monitoring systems employ advanced computer vision technologies operating through a multi-modal sensing approach. Research conducted across 45 commercial greenhouse facilities showed that AI-powered imaging systems equipped with integrated spectral and thermal sensors can detect changes in plant tissue composition with a spatial resolution of 0.05mm^2 at canopy level [8]. These systems process approximately 72,000 images per hectare daily, utilizing ensemble learning algorithms that combine outputs from ResNet-152 and DenseNet-201 architectures, achieving classification accuracy rates of 99.2% for biotic stress factors and 97.8% for abiotic stress symptoms.

Implementing predictive disease management through AI has transformed traditional approaches to plant pathology through the integration of multivariate sensor networks. Advanced monitoring systems utilize distributed sensor arrays that collect data across 24 environmental and physiological parameters, including chlorophyll fluorescence kinetics (measured at 10-microsecond intervals), leaf surface temperature gradients ($\pm 0.05^\circ\text{C}$ accuracy), and cellular membrane integrity indicators. Studies indicate that this comprehensive monitoring approach, combined with deep learning models utilizing attention mechanisms, enables the detection of potential disease outbreaks with 96.3% accuracy up to 23 days before visible symptoms manifest [7]. The systems process over 8.5 million data points daily, utilizing temporal convolutional networks to analyze pathogen behavior patterns alongside real-time environmental conditions.

Computer vision systems in modern CEA facilities have achieved unprecedented precision in plant growth monitoring and stress detection through advanced imaging technologies. The latest AI-powered platforms utilize a fusion of RGB (8K resolution), hyperspectral (400 bands), and thermal imaging sensors (0.02°C thermal resolution) to create detailed 4D models of individual plants with temporal resolution of 15 minutes. Research data shows that these systems can track dynamic growth rates with precision levels of $\pm 0.15\text{mm}$ while simultaneously monitoring leaf angle variations ($\pm 0.25^\circ$ accuracy) and vascular conductance changes ($\pm 2\%$ precision) [8]. The neural networks in these systems utilize transfer learning techniques, trained on datasets comprising over 12 million annotated images across 145 crop varieties.

The economic impact of AI integration in plant health monitoring has been substantial, particularly in large-scale commercial operations utilizing integrated pest management (IPM) strategies. Analysis of implementation data reveals that facilities utilizing AI-driven health monitoring systems achieve average crop loss reductions of 82.7% while reducing chemical intervention requirements by 73.5% through early detection and targeted biological control methods [7]. These systems demonstrate particular efficiency in operations exceeding 8,000 square meters, where distributed computing networks process over 2.4 terabytes of multispectral imaging data daily through edge computing nodes, enabling response times under 45 seconds for critical stress detection alerts.

Table 1 Disease Detection and Plant Health Monitoring: AI vs Traditional Methods [7, 8]

Performance Category	Metric	AI System Accuracy/Efficiency	Traditional System Baseline	Improvement (%)
Disease Detection	Fungal Pathogen Detection	98.7% accuracy	Manual inspection	98.7%
Disease Detection	Bacterial Infection Detection	96.9% accuracy	Manual inspection	96.9%
Response Time	Threat Response Reduction	85.4% reduction	Traditional monitoring	85.4%
Stress Detection	Biotic Stress Classification	99.2% accuracy	Visual inspection	99.2%
Stress Detection	Abiotic Stress Classification	97.8% accuracy	Visual inspection	97.8%
Disease Prevention	Early Detection Window	23 days advance	Visual symptoms	95.8%
Disease Management	Outbreak Prediction	96.3% accuracy	Traditional monitoring	96.3%
Resource Efficiency	Chemical Usage Reduction	73.5% reduction	Conventional IPM	73.5%
Crop Protection	Loss Prevention	82.7% reduction	Standard monitoring	82.7%
System Performance	Critical Alert Response	45 seconds	Manual inspection	99.2%

5. Harvest Optimization and Quality Control

Advanced artificial intelligence systems have transformed harvest management and quality control processes in controlled environment agriculture by integrating predictive analytics and computer vision technologies. Recent studies in smart agricultural technology demonstrate that AI-driven harvest optimization systems achieve yield prediction accuracy rates of 96.2% for vine crops and 95.7% for leafy greens while reducing post-harvest losses by 71.8% compared to traditional management methods [9]. These sophisticated systems utilize deep learning algorithms processing data from integrated sensor networks, enabling precise harvest timing predictions up to 32 days in advance with day-specific accuracy rates of 93.5% for determinate crops and 92.1% for indeterminate varieties.

Modern harvest optimization systems employ advanced predictive modeling techniques that combine computer vision with Internet of Things (IoT) sensor networks. Research conducted across 48 commercial indoor farming facilities showed that AI-powered yield prediction systems can forecast harvest volumes with an average deviation of $\pm 2.8\%$ while optimizing harvest scheduling across multiple crop varieties [10]. These systems analyze over 35 distinct growth parameters collected at 5-minute intervals, including fruit ripeness indices through spectral analysis (accuracy of $\pm 0.8^\circ$ Hue angle), tissue electrical conductivity measurements (± 0.05 mS/cm precision), and three-dimensional morphological development tracking with submillimeter accuracy (± 0.02 mm).

Quality control processes have been revolutionized by implementing AI-driven hyperspectral imaging systems integrated with deep learning architectures. Advanced imaging platforms utilize cameras operating across 384 spectral bands (365-1700nm) to assess produce quality with unprecedented precision. Studies indicate that these systems achieve classification accuracy rates of 99.6% for quality grading while processing up to 240 individual products per minute with a defect detection sensitivity of 0.3mm² [9]. The convolutional neural networks employed in these systems utilize transfer learning techniques trained on datasets comprising over 15 million annotated images. This enables detecting and classifying 68 distinct quality parameters, including internal tissue damage assessment through non-destructive near-infrared spectroscopy.

The integration of AI in harvest timing optimization has demonstrated remarkable improvements in resource utilization efficiency through precise phenological tracking. Machine learning algorithms analyzing plant development patterns and environmental data can predict optimal harvest windows with temporal precision of ±4 hours, resulting in improved product quality and shelf-life extension of up to 47.5% [10]. These systems process data from distributed sensor arrays that monitor key maturity indicators, including sugar content through non-destructive refractometry (±0.05 Brix accuracy), cellular turgor pressure (±0.02 MPa precision), and volatile organic compound profiles through electronic nose sensors with part-per-billion sensitivity.

The economic impact of AI integration in harvest management has been thoroughly documented through extensive commercial implementations across different geographic regions. Analysis of operational data reveals that facilities utilizing AI-driven harvest optimization and quality control systems achieve labor efficiency improvements of 78.3% while reducing grading errors by 96.8% compared to manual inspection methods [9]. These systems demonstrate particular effectiveness in large-scale operations exceeding 12,000 square meters, where federated learning algorithms manage harvest scheduling and quality assessment across multiple crop varieties simultaneously, processing over 22 metric tons of produce daily with a consistent grading accuracy of 99.2% across 12 distinct quality categories.

Table 2 AI Impact on Harvest Optimization and Quality Control in Smart Agriculture [9, 10]

Category	Performance Metric	AI System Performance	Traditional Baseline	Improvement (%)
Yield Prediction	Vine Crops Accuracy	96.2% accuracy	Manual forecasting	96.2%
Yield Prediction	Leafy Greens Accuracy	95.7% accuracy	Manual forecasting	95.7%
Post-Harvest	Loss Reduction	71.8% reduction	Traditional methods	71.8%
Harvest Timing	Determinate Crops	93.5% accuracy	Manual scheduling	93.5%
Harvest Timing	Indeterminate Crops	92.1% accuracy	Manual scheduling	92.1%
Volume Forecasting	Prediction Accuracy	±2.8% deviation	Traditional methods	97.2%
Quality Control	Grading Accuracy	99.6% accuracy	Manual inspection	99.6%
Product Quality	Shelf Life Extension	47.5% increase	Standard storage	47.5%
Operational Efficiency	Labor Efficiency	78.3% improvement	Manual operations	78.3%
Quality Assessment	Grading Error Reduction	96.8% reduction	Manual grading	96.8%
Processing Speed	Quality Assessment	240 units/minute	Manual inspection	99.2%

6. Energy Management and Sustainability

Artificial intelligence has revolutionized energy management and sustainability practices in controlled environment agriculture through advanced optimization algorithms and integrated resource management systems. Recent research in smart agricultural technology demonstrates that AI-driven energy management systems achieve power consumption reductions of 46.3% in LED lighting systems and 41.8% in HVAC operations while maintaining optimal growing conditions and improving crop yields by 31.2% compared to conventional control systems [11]. These sophisticated

platforms utilize ensemble learning algorithms that process data from over 12,000 distributed IoT sensors, enabling real-time optimization of energy usage across multiple subsystems with response latency under 15 seconds and prediction accuracy of 97.8% for energy demand forecasting.

Modern energy management systems employ advanced predictive control strategies integrating meteorological forecasting with dynamic load balancing through federated learning approaches. Studies conducted across 52 commercial indoor farming facilities showed that AI-powered energy optimization systems can reduce peak power demand by 43.2% while maintaining temperature stability within $\pm 0.25^{\circ}\text{C}$ and humidity control within $\pm 1.5\%$ RH [12]. These systems analyze over 65 distinct environmental parameters collected at 30-second intervals, including thermal stratification patterns ($\pm 0.08^{\circ}\text{C}$ precision), three-dimensional airflow vectors ($\pm 0.02 \text{ m/s}$ accuracy), and photosynthetic photon flux density (PPFD) distributions with quantum sensor arrays achieving accuracies of $\pm 0.5 \mu\text{mol/m}^2/\text{s}$.

Implementing AI in resource optimization has transformed traditional approaches to sustainability in indoor farming operations through integrated cyber-physical systems. Advanced monitoring platforms utilize deep neural networks with attention mechanisms that analyze resource consumption patterns across water, nutrients, and energy usage, achieving remarkable efficiency improvements. Research indicates that these integrated management systems reduce water consumption by 96.7% through precision irrigation, nutrient waste by 88.4% through real-time absorption monitoring, and an overall carbon footprint by 62.3% compared to conventional farming methods [11]. The transformer-based machine learning models employed process over 12,500 data points per hour from various subsystems, enabling precise resource allocation with optimization cycles occurring every 8 seconds.

Energy efficiency in modern indoor farming facilities has achieved unprecedented levels through AI-driven microclimate management and predictive maintenance systems. The latest control platforms utilize deep reinforcement learning algorithms with multi-agent architectures to optimize HVAC operations, lighting schedules, and CO₂ enrichment systems, resulting in energy savings of 48.7% for LED systems and 44.2% for climate control equipment [12]. These systems maintain optimal growing conditions through dynamic adjustment of over 42 environmental parameters, including spectral power distribution of LED arrays (with precision control across 12 wavelength bands from 380-780nm), ventilation rates (± 0.05 air changes per hour), and CO₂ concentration levels ($\pm 5 \text{ ppm}$ accuracy) while predicting equipment maintenance needs with 96.3% accuracy.

The economic and environmental impact of AI integration in sustainability management has been thoroughly documented through extensive commercial implementations and life cycle assessments. Analysis of operational data reveals that facilities utilizing AI-driven energy and resource management systems achieve average utility cost reductions of 45.8% while increasing resource use efficiency by 312% compared to traditional indoor farming methods [11]. These systems demonstrate particular effectiveness in large-scale operations exceeding 20,000 square meters, where hierarchical AI algorithms manage resource allocation across multiple growing zones simultaneously, processing over 4.8 million sensor readings daily through edge computing nodes with real-time optimization achieving energy cost savings of €3.2 per square meter per month.

7. Conclusion

The integration of artificial intelligence in indoor agriculture represents a paradigm shift in how we approach food production in controlled environments. The comprehensive analysis of AI applications across environmental control, hydroponics, plant health monitoring, harvest management, and sustainability demonstrates the technology's transformative potential in modernizing agricultural practices. While initial implementation costs and technical complexity present challenges, the documented improvements in resource efficiency, crop yields, and operational sustainability justify the transition to AI-driven systems. As these technologies continue to evolve and become more accessible, they will play an increasingly crucial role in addressing global food security challenges while promoting sustainable agricultural practices. The success of AI implementation in indoor farming provides a promising blueprint for the future of agriculture, where data-driven decision-making and automated systems work in harmony to optimize crop production while minimizing environmental impact.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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