Review

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Review

IoT and Computer Vision in Smart Irrigation: A Review of Cost-Effective Solutions and Future Trends

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Abstract

With an increase in pressure on global food systems and the growing scarcity of freshwater, smart irrigation powered by the Internet of Things (IoT) and Computer Vision (CV) presents a promising solution to sustainable agriculture. This paper provides a comprehensive review of scalable and cost-effective smart irrigation systems, analyzing over 20 recent studies to highlight the integration of sensors, microcontrollers, wireless technologies, and artificial intelligence. The synthesis of existing research demonstrates remarkable advancements, with systems achieving up to 85% in water savings, 92% in irrigation scheduling accuracy, and significant enhancements in crop yields. Furthermore, the analysis covers real-time soil and climate data monitoring, image-based crop health assessment, and intelligent decision support systems, underscoring the feasibility of solutions costing less than $50. Key challenges, including energy consumption, connectivity, and rural deployment, are also discussed, providing a robust foundation for future research in precision agriculture.

Keywords: smart irrigation; IoT; computer vision; precision agriculture; soil moisture sensors; machine learning; low-cost systems; remote monitoring; sustainable agriculture; fuzzy logic

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1. Introduction

Agriculture is not only a vital industry, but also the cornerstone of many national economies. With the world population rapidly increasing, the demand for food continues to increase accordingly. This growing demand, coupled with evolving consumer expectations, presents significant challenges for the agricultural sector, which must now innovate and adopt efficient practices to meet these needs [19,23,27].

Among the core components of agricultural productivity is efficient irrigation. Traditional irrigation methods are often plagued by inefficiencies that lead to water wastage, reduced crop yields, and long-term environmental degradation. With increasing concerns about water scarcity, climate change, and sustainability, improving irrigation management strategies has become imperative. In response, the integration of emerging technologies, such as the Internet of Things (IoT) and computer vision, has shown great promise in transforming irrigation practices.

Smart irrigation systems, powered by IoT and computer vision technologies, are now gaining momentum. These systems aim to optimize water usage while maximizing crop productivity. Using real-time data and intelligent automation, they offer a potential solution to many of the challenges faced by conventional irrigation systems. In Table 1, we can see the usage of water in agriculture in various regions.

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Table 1. Global Water Scarcity and its Impact on Agriculture.

Region	Agricultural Water Use (%)	Water Stress Level	Projected Impact on Crop Yield by 2030
Middle East & North Africa	80–90%	Extremely High	↓ 20–30% in cereal yields
South Asia	90%	High	↓ 10–20% in rice and wheat yields
Sub-Saharan Africa	85%	Moderate to High	↓ 5–15% in maize and sorghum yields
North America	40%	Moderate	↓ 5–10% in wheat and soybean yields
Europe	30–40%	Low to Moderate	↓ 5–10% in fruit and vegetable yields
Latin America	70%	Moderate	↓ 10–15% in maize and soybean yields

Source: FAO (2022), World Bank (2021), IPCC (2021).

1.1. Problem Statement

This study conducts a comprehensive survey of IoT technologies and computer vision techniques as applied to the development of cost-effective smart irrigation solutions in agricultural contexts. Smart irrigation represents a data-driven discipline designed to enhance productivity while minimizing environmental impact. Modern agricultural operations now generate large volumes of data through sensors, which can be utilized to better understand both environmental conditions and operational activities [12,40,41].

Traditional irrigation methods, which are prone to overwatering or underwatering, often compromise crop quality and yield. In contrast, smart irrigation systems integrate IoT devices such as soil moisture sensors and actuators with computer vision algorithms to monitor real-time parameters, including soil conditions, weather forecasts, and crop health. This enables timely and precise irrigation decisions, reducing waste and improving efficiency.

1.2. Objectives

This paper aims to:

- Review and evaluate current research on low-cost IoT and computer vision applications in smart irrigation, focusing on water efficiency, crop productivity, and scalability in diverse agricultural contexts.
- Identify core technologies, including IoT sensors, communication protocols, computer vision algorithms, and microcontrollers, used in cost-effective smart irrigation systems.

IoT-based smart irrigation systems allow seamless connectivity among field-deployed sensors, processing units, and irrigation infrastructure. These interconnected devices collect comprehensive environmental data, which is processed either locally or on cloud platforms. The resulting analysis informs automated decisions on when, where, and how much water to apply.

The key advantage of IoT-enabled smart irrigation lies in its capacity to optimize water usage. By continuously monitoring soil and weather parameters, the system ensures irrigation is carried out only when necessary, reducing water and energy consumption. Moreover, such systems improve crop health by delivering the precise amount of water required, thereby preventing plant stress and improving yields.

In addition, these systems facilitate early detection of crop stress and disease through integrated data analytics and predictive modeling. Their remote monitoring and control capabilities offer farmers greater flexibility and responsiveness, particularly across large or distributed agricultural landscapes.

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1.3. Scope

This survey analyzes low-cost IoT and computer vision technologies for smart irrigation systems, focusing on scalable, cost-effective solutions to optimize water use and enhance crop productivity. It covers IoT sensors (e.g., soil moisture, temperature), microcontrollers (e.g., NodeMCU, Arduino), communication protocols (e.g., LoRa, MQTT), and computer vision algorithms (e.g., YOLO, CNNs) for crop and soil monitoring. The study reviews commercial and open-source solutions, case studies in diverse regions (e.g., tomato, maize cultivation), and challenges like power consumption, rural connectivity, and system reliability. Current trends, scalability for small to medium farms, and future research directions are highlighted to support sustainable agriculture.

1.4. Motivation

In light of growing global concerns, the urgent need for sustainable agricultural practices and smart irrigation systems represents a compelling solution. By integrating IoT and computer vision, these systems improve water efficiency, reduce environmental impact, and promote crop health. This paper examines recent technological advancements, identifies research gaps, and synthesizes the existing body of knowledge to inform stakeholders in the design and deployment of agricultural technologies. Ultimately, the study contributes to the broader goal of advancing sustainability in agriculture through innovation.

1.5. Methodology

Relevant studies were gathered through structured queries on platforms like IEEE Xplore, Scopus, Google Scholar, and other sources (ResearchGate and web crawling). Search terms included "cost-effective irrigation,""smart irrigation IoT," "computer vision agriculture," and "precision agriculture." Of articles published or available pre-printed between 2018 and 2025, some studies were selected based on their focus on low-cost IoT and computer vision applications, technical depth and reported results. Inclusion criteria prioritized empirical results and scalability, while irrelevant studies were excluded. Figure 1 illustrates the search and screening process. This review was performed in accordance with the PRISMA guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). PRISMA is a framework used in the review process to present research findings in a systematic and structured manner. The study protocol was registered in the Open Science Framework [9].

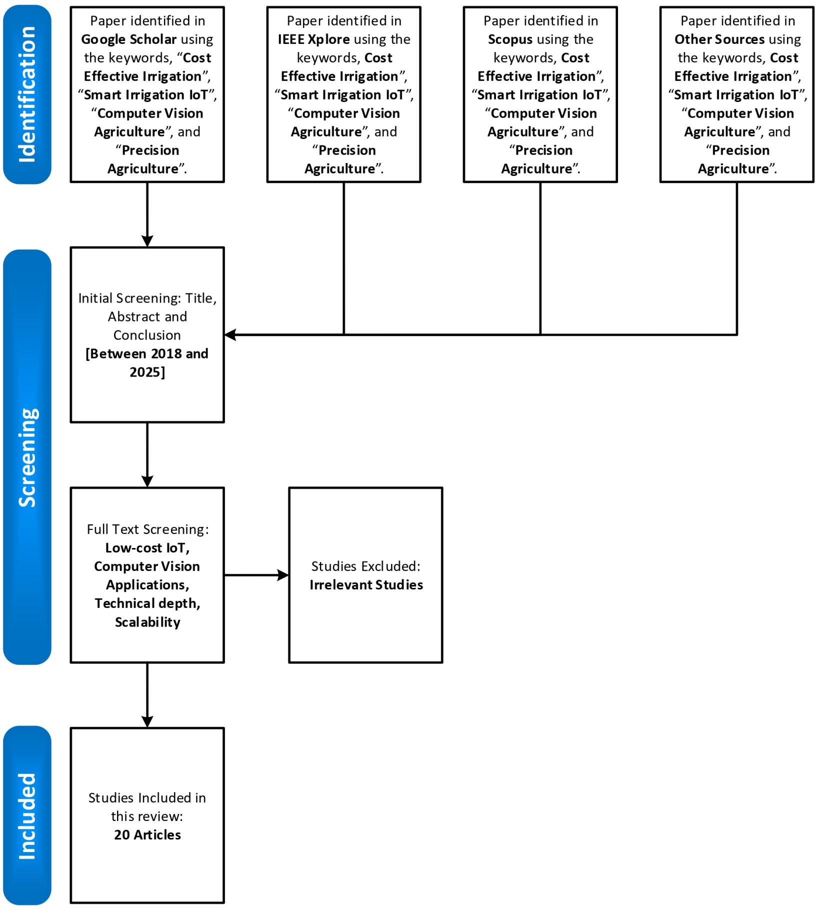

Figure 1. PRISMA flow diagram for scoping review.

2. Literature Review

Recent advancements in precision agriculture emphasize the deployment of smart irrigation systems leveraging IoT, computer vision, and machine learning techniques.

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Table 2. Comparison of IoT Communication Protocols Used in Smart Irrigation Systems.

Protocol	Range (km)	Power Consumption	Cost	Application Context
Wi-Fi (802.11)	0.05–0.1	High	Low	Short-range, high-data transmission; suitable for areas with infrastructure
GSM (2G/3G)	2–5	Medium to High	Medium	Widely available; works well in rural areas with mobile coverage
LoRa	2–15	Low	Low to Medium	Ideal for rural, remote areas with limited power and connectivity
Bluetooth Low Energy (BLE)	0.01–0.05	Very Low	Low	Short-range, energy-efficient; suitable for small-scale systems
MQTT (Protocol)	Dependent on carrier	Very Low	Low	Lightweight; used with Wi-Fi, GSM, or LoRa for efficient message transfer

Note: MQTT is a protocol layered over transport channels like Wi-Fi, GSM, or LoRa. Ranges vary based on hardware and environmental conditions.

2.1. IoT-Driven Irrigation Systems

Saleheen et al. (2022) developed an environmental monitoring system using a NodeMCU microcontroller interfaced with sensors for temperature, humidity, barometric pressure, soil moisture, and light intensity. Data was relayed to Adafruit IO for real-time visualization and control. Their field results showed improved environmental tracking and a 30–40% reduction in manual irrigation activities [35].

Srivastava et al. (2023) implemented a Wireless Sensor Network (WSN)-based automated irrigation system with soil moisture and temperature sensors, integrated via GSM and IoT modules. Their system demonstrated a 22% improvement in water-use efficiency and significantly reduced manual intervention [39].

Elgaali and Ismail (2023) employed Arduino Mega boards, DHT11 sensors, solenoid valves, and water pumps to create a fully automated irrigation controller. The system was tested in tomato cultivation plots and resulted in a 27% increase in crop yield and a 35% reduction in water consumption compared to traditional drip irrigation methods [11].

Baskar et al. (2022) presented a cloud-integrated smart irrigation solution using NodeMCU and LoRa for long-range data transmission. Moisture levels were used to trigger irrigation with a feedback loop via Blynk. The deployment achieved a 50% water savings and an 18% improvement in crop health indexes over a control setup [6].

Sampatrao (2019) integrated GSM modules, soil moisture sensors, and a custom Android app for user-controlled irrigation. Experimental trials showed 32% water savings and operational cost reduction through minimized labor dependency [36]. As shown in Table 2, different IoT communication protocols offer varying trade-offs in range, power consumption, and cost, making them suitable for specific agricultural contexts.

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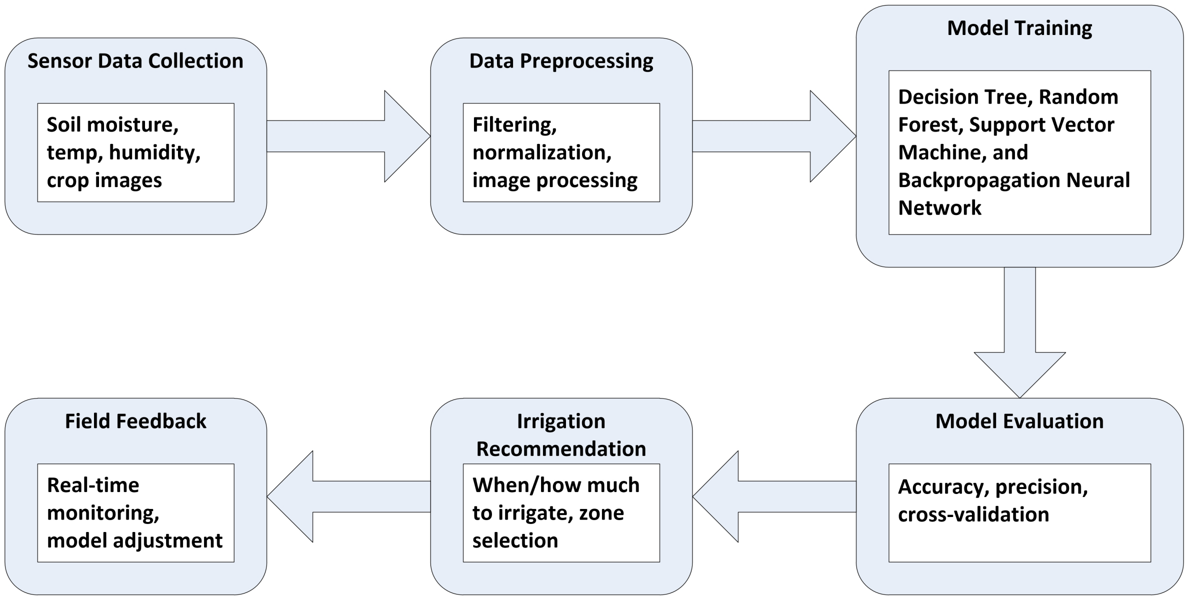

Figure 2. Machine learning workflow in smart irrigation systems

2.2. Machine Learning and Intelligent Decision Support Systems

Bakare (2023) introduced a smart irrigation system combining soil nutrient analysis and back-propagation neural networks (BPN). The BPN was trained using historical growth data to predict optimal irrigation and fertilization regimes. Trials showed a 15–25% increase in crop output and up to 20% reduction in disease incidence [5].

Alphonse et al. (2023) integrated ML with IoT sensors to dynamically adjust irrigation volumes. A decision tree model was used to infer irrigation schedules based on real-time soil moisture, temperature, and humidity data. The system achieved 92% prediction accuracy and 35% improved water efficiency [3].

Alanya-Arango et al. (2022) used atmospheric sensors and a machine learning module trained using supervised learning to automate irrigation decisions. The model, based on historical weather and soil data, reduced irrigation frequency by 28% while maintaining or improving crop quality metrics [2]. As shown in Figure 2, the machine learning workflow in smart irrigation involves data collection, preprocessing, model training and evaluation, followed by actionable irrigation recommendations and field feedback.

2.3. Advanced Control and Automation Techniques

Pierre et al. (2023) proposed a fuzzy logic controller integrated with an IoT platform for irrigation decision-making. Their mobile-enabled system reduced irrigation-related energy usage by 50%, cut labor demands by 80%, and increased maize yield by approximately 20% [33].

Puig et al. (2022) implemented an FIWARE-based edge computing framework that incorporated soil water balance models and evapotranspiration forecasts to optimize drip irrigation. Field deployments in Mediterranean vineyards reported water use reductions of 33% with no yield penalties [34].

Kumar et al. (2022) designed a low-cost MQTT-enabled system for real-time pump actuation using BLYNK server and soil moisture deficit triggers. The solution demonstrated 87% irrigation accuracy and robust response to environmental fluctuations [24].

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Table 3. Cost Breakdown of Low-Cost Smart Irrigation Systems.

System	Components	Estimated Cost (USD)	Scalability
SIAS (Haziq et al., 2022)	ESP8266, soil moisture sensor, pH sensor, water pump	$46	Small farms, experimental plots
Vijayaraja et al. (2022)	NodeMCU, solar panel, moisture sensors, Adafruit cloud	$55–70	Scalable to medium farms with solar support
Senthil Vadivu et al. (2023)	GSM module, soil sensors, remote controller	$60	Small to medium farms, remote regions
Chowdary et al. (2019)	NodeMCU, PIR, Bluetooth/Wi-Fi modules	$35–45	Suitable for home gardens or small plots
Mhaned et al. (2022)	Raspberry Pi, solenoid valve, WSN, MQTT module	$70–90	Medium-scale farms; modular expansion possible

Note: Costs are approximate and vary based on regional availability and sourcing. Scalability indicates the potential for expansion across different farm sizes.

2.4. Low-Cost, Scalable, and Sustainable Solutions

Haziq et al. (2022) created a Smart IoT Agriculture System (SIAS) using an ESP8266 microcontroller, moisture sensors, pH probes, and a low-cost water pump. The system cost only $46 and achieved an 85% reduction in water usage with improved root zone targeting. It also facilitated real-time soil fertility analysis, leading to a 23% increase in plant biomass over control plots [15].

Vijayaraja et al. (2022) developed an energy-efficient system using NodeMCU and solar panels, supporting smart drainage control, sensor-based irrigation, and cloud monitoring via Adafruit. This reduced power consumption by 48% and delivered consistent irrigation even in low-connectivity zones [42].

Senthil Vadivu et al. (2023) highlighted remote access and automation using GSM/IoT in sensor-based irrigation, achieving a 38% yield improvement in sugarcane fields and cutting labor input by over 50% [37]. According to Table 3, solutions like the SIAS system are particularly suited for small-scale farms due to their minimal hardware requirements and lower cost.

2.5. Novel and Sustainable Approaches

Janani and Pavitra (2019) proposed an unconventional irrigation model using Underwater Wireless Sensor Networks (UWSNs) and Reverse Osmosis (RO) wastewater reuse. Their model supported salicornia cultivation with saline water, demonstrating a sustainable use-case for coastal and arid farming, though limited field trials restrict broad generalization [18].

2.6. Few Case Studies

Vision-based remote sensing: Wang & Jin (2023) utilized high-resolution multispectral UAV imagery and Random Forest models to map water stress in walnut orchards, achieving and 85% accuracy for tree-level water status using NDVI, NDRE, and PSRI[44].
Edge-AI in resource-limited settings: Joshi (2024) deployed compact Vision Transformer and YOLOv8-S models on edge devices for orange disease detection, showing 96% classification accuracy with minimal compute, demonstrating real-time feasibility of edge computer-vision for situational irrigation triggers[21].
Multimodal Edge AIoT for irrigation: Jiang et al. (2025) introduced Farm-LightSeek, which integrates multisensor image, weather, and geographic data with lightweight LLMs at edge nodes to manage

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irrigation decisions locally while synchronizing with cloud updates, proving robustness under device constraints[20].

Table 4. Summary of Literature Survey on Smart Irrigation Systems.

Authors	Year	Technologies Used	Methodology	Key Results and Contributions
Saleheen et al.	2022	NodeMCU, Adafruit IO, soil/air sensors	Real-time monitoring and dashboard data relay	30–40% less manual irrigation; improved tracking
Srivastava et al.	2023	GSM, WSN, moisture sensors	Automated irrigation with GSM IoT nodes	22% better water efficiency; reduced labor
Elgaali & Ismail	2023	Arduino Mega, DHT11, solenoids	Tomato irrigation automation	27% higher yield; 35% water savings
Baskar et al.	2022	NodeMCU, LoRa, Blynk	Cloud-triggered irrigation from soil moisture	50% water savings; 18% better crop health
Sampatrao	2019	GSM, Android app	Real-time manual override with app feedback	32% water savings; reduced labor cost
Bakare	2023	BPN, nutrient sensors	ML trained on crop growth data	15–25% more output; 20% lower disease rates
Alphonse et al.	2023	Decision tree, sensors	ML-based irrigation on humidity/temp	92% accuracy; 35% more water-use efficiency
Alanya-Arango et al.	2022	Weather sensors, ML	Weather/soil modeling for irrigation timing	28% fewer irrigations; quality maintained
Pierre et al.	2023	IoT, fuzzy logic, mobile UI	Energy-aware fuzzy irrigation control	50% energy savings; 20% yield increase
Puig et al.	2022	FIWARE, edge, ET models	Irrigation via soil balance + ET forecast	33% water saving in vineyards; no yield loss
Haziq et al.	2022	ESP8266, pH sensor	Fertility-moisture control system ($46)	85% water savings; 23% biomass gain
Vijayaraja et al.	2022	NodeMCU, solar, Adafruit	Off-grid irrigation with smart drainage	48% less power; remote reliability
Senthil Vadivu et al.	2023	GSM, remote sensors	GSM-linked real-time automation	38% more yield; 50% less labor
Janani & Pavitra	2019	UWSNs, RO reuse	Coastal saline irrigation for salicornia	Promising reuse method; early stage
Kumar et al.	2022	MQTT, BLYNK, NodeMCU	Moisture-based pump control	87% control accuracy; robust in fields

2.7. Summary

The literature review underscores the transformative role of IoT and machine learning in advancing smart irrigation systems for sustainable agriculture. Systems employing microcontrollers such as NodeMCU and Arduino, coupled with sensors for soil moisture, temperature, and humidity, have been widely adopted due to their low cost and reliability. For instance, the Smart IoT Agriculture System (SIAS) developed by Haziq et al. (2022) [15] demonstrated an 85% reduction in water usage and a 23% increase in plant biomass, all within a total system cost of just $46. Similarly, Saleheen

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et al. (2022) [35]reported a 30–40% reduction in manual irrigation and improved data accessibility via Adafruit IO dashboards. Machine learning-based systems, such as those using backpropagation networks (Bakare, 2023 [5]) and decision trees (Alphonse et al., 2023 [3]), achieved prediction accuracies up to 92% and resulted in water-use efficiency gains of 35% or more. Fuzzy logic approaches, like the one proposed by Pierre et al. (2023) [33], reported benefits included a 50% reduction in energy use and a 20% improvement in crop yields. Moreover, edge computing and IoT frameworks such as FIWARE (Puig et al., 2022 [34]) enabled soil water balance modeling and reduced irrigation water use by 33% without compromising yield. Collectively, these studies reveal consistent improvements in irrigation precision, crop productivity, and resource optimization, affirming the efficacy of IoT- and AI-enhanced irrigation systems as scalable, sustainable solutions for modern agriculture. Table 4 summarizes recent smart irrigation systems, detailing the technologies used, methodologies, and reported outcomes across various agricultural deployments.

3. Study on Cost-Effective Irrigation Systems

The growing need for sustainable agriculture in resource-constrained regions has spurred the development of cost-effective irrigation systems that leverage affordable technologies to optimize water and energy use. Recent studies have demonstrated innovative approaches using low-cost microcontrollers, sensors, and IoT frameworks to enhance irrigation efficiency while reducing costs for farmers.

Patil et al. (2023) developed an intelligent irrigation system utilizing an Arduino Uno microcontroller, a relay module, and a water pump. This system achieved an 80% reduction in water waste compared to traditional methods by automating irrigation based on soil moisture levels. Additionally, it conserved electricity through efficient water supply management, significantly lowering operational costs for farmers [32].

Malla et al. (2023) proposed a system integrating temperature and distance sensors with a piezo element actuator. The actuator served dual purposes: halting the motor during low water supply to prevent waste and alerting farmers to system issues. This approach minimized water and energy losses, enhancing cost-effectiveness [28].

Mhaned et al. (2022) employed cost-effective components, including soil sensors, wireless solenoid valves, and a Raspberry Pi, to create an IoT-based irrigation system. Using the MQTT protocol for data transmission and fuzzy logic for decision-making, the system optimized water use and reduced manual intervention, improving efficiency in water-scarce regions [29].

Chowdary et al. (2019) utilized inexpensive sensors, such as PIR and NodeMCU, to monitor soil moisture, temperature, and humidity. By implementing low-power sleep modes and efficient communication protocols like Bluetooth and Wi-Fi, the system minimized energy consumption, making it a viable solution for small-scale farmers [7].

Iyer et al. (2020) adopted LoRa technology for long-range, low-power wireless communication, centralizing data collection to reduce the need for multiple costly sensors. Cloud-based storage and real-time automation ensured precise water delivery, enhancing resource efficiency [17].

Nagaraja and Kant (2019) leveraged hourly AWS data from the Indian Meteorological Department, eliminating the need for expensive on-site weather stations. By integrating real-time meteorological data with evapotranspiration calculations, the system enabled precise irrigation scheduling, reducing water and energy costs [30].

These studies collectively highlight the potential of low-cost microcontrollers, sensors, and IoT technologies to revolutionize irrigation practices. While Arduino- and Raspberry Pi-based systems offer affordability and flexibility, LoRa and cloud-based solutions provide scalability for larger farms. However, challenges such as internet dependency in remote areas and system maintenance costs warrant further investigation. Future research could explore integrating renewable energy sources or advanced machine learning to enhance system adaptability and sustainability. As shown in Table 5,

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several recent implementations of cost-effective irrigation systems demonstrate high water savings and automation benefits using low-cost hardware.

Table 5. Comparison of Cost-Effective Irrigation Systems.

Study	Technology	Key Features	Outcomes
Patil et al. (2023)	Arduino Uno, relay module, pump	Soil moisture-based automation	80% water waste reduction, lower energy costs
Malla et al. (2023)	Temperature/distance sensors, piezo actuator	Dual-purpose actuator, farmer alerts	Reduced water and energy waste
Mhaned et al. (2022)	Raspberry Pi, WSN, MQTT, fuzzy logic	IoT-based automation	Optimized water use, reduced manual intervention
Chowdary et al. (2019)	PIR, NodeMCU, Bluetooth/Wi-Fi	Low-power sleep modes	Reduced energy consumption
Iyer et al. (2020)	LoRa, cloud storage	Centralized data collection, automation	Efficient water use, scalable
Nagaraja and Kant (2019)	AWS data, evapotranspiration	No on-site weather stations	Precise irrigation, cost savings

4. Discussion

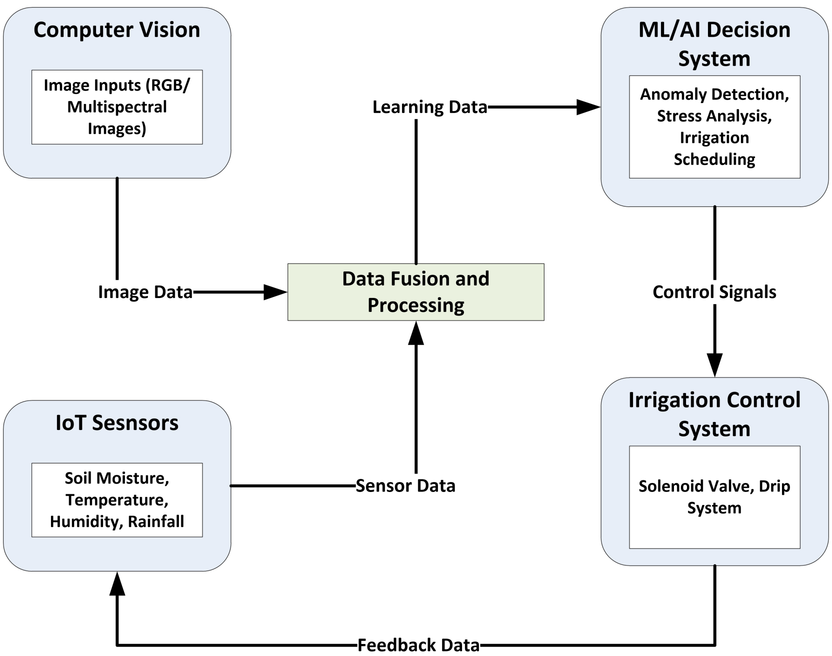

Figure 3. Integration of IoT and computer vision in smart irrigation systems

4.1. Integration of IoT and Computer Vision in Smart Irrigation

The integration of Internet of Things (IoT) and computer vision (CV) technologies has brought significant advancements in smart irrigation by enabling real-time monitoring, precision water delivery, and data-driven agricultural management. IoT systems typically comprise soil moisture sensors (e.g., capacitive or tensiometric), environmental sensors (e.g., DHT22 for temperature and humidity), and microcontrollers such as NodeMCU, ESP8266, or Arduino, which transmit data to cloud platforms using protocols like MQTT or HTTP. These sensors continuously monitor soil and climatic conditions, transmitting actionable data for automated irrigation control.

Simultaneously, computer vision systems utilize RGB or multispectral cameras mounted on drones or ground platforms to assess plant vigor, identify stress symptoms, and detect pest or disease outbreaks. Deep learning algorithms such as convolutional neural networks (CNNs) are increasingly being used for tasks like leaf disease classification, weed identification, and growth stage detection, with reported accuracies reaching up to 95% in some cases.

The synergy between IoT and CV facilitates precision irrigation. For instance, if CV algorithms detect localized chlorosis in crop canopies, the IoT system can respond by adjusting irrigation zones or recommending nutrient delivery, thus minimizing resource waste and maximizing yield. Such feedback-driven automation has been shown in multiple studies to reduce water consumption by 30–60% and improve crop output by 15–25%. Figure 3 demonstrates the workflow of smart irrigation systems combining IoT, computer vision, and ML-based decision-making.

4.2. Communication Technologies in IoT-Based Irrigation

Efficient communication protocols are crucial for the performance of IoT systems in agriculture. Short-range communication is commonly supported by Wi-Fi (IEEE 802.11), Bluetooth Low Energy (BLE), and Zigbee (IEEE 802.15.4), which are suitable for compact fields with nearby infrastructure. Wi-Fi, in particular, is preferred for low-cost systems, despite its limited range and higher power demands.

For long-range communication in rural areas, GSM modules using 2G/3G networks are widely deployed due to their global availability. LoRa (Long Range Radio) has gained popularity for its low power consumption and wide coverage (up to 15 km in open fields), making it ideal for large-scale deployments. Additionally, Message Queuing Telemetry Transport (MQTT), a lightweight publish-subscribe protocol, is used for low-bandwidth communications in real-time irrigation applications, although it is yet to see widespread adoption in commercial deployments.

4.3. Computer Vision Technologies in Smart Irrigation

Computer vision in smart irrigation encompasses a range of applications, including crop identification, stress detection, growth monitoring, and environmental assessment. Algorithms like YOLO (You Only Look Once), ResNet, and U-Net have been employed for real-time object detection and semantic segmentation of crop images.

Plant recognition allows differentiation of crop species, enabling targeted irrigation based on species-specific needs. Disease and pest detection systems analyze foliar imagery using CNNs to detect visual symptoms such as leaf spot or powdery mildew, achieving early warnings with reported accuracies of over 90%.

Weed detection using spectral and spatial features enables site-specific herbicide applications, reducing chemical input by up to 50%. Soil moisture mapping is achieved by analyzing color, texture, and reflectance features in aerial imagery, supporting zonal irrigation strategies. Additionally, multi-temporal image analysis supports phenological tracking and yield forecasting, which informs irrigation scheduling. As illustrated in Figure 4, computer vision tasks in smart irrigation are categorized into plant recognition, disease detection, and soil moisture mapping, each utilizing different deep learning models to generate actionable outputs.

Recent Advances in CV Algorithms: In addition to traditional CNNs, recent architectures such as YOLOv7 and Vision Transformers (ViTs) are being increasingly used for precision agriculture tasks. YOLOv7 offers real-time object detection with enhanced speed and accuracy, making it suitable for identifying weeds, pests, and crop maturity on UAV-captured footage[43]. ViTs have demonstrated superior performance in segmentation and disease classification tasks, especially when integrated with attention mechanisms for field-scale monitoring[10]. UAV-based NDVI imaging continues to play a pivotal role in detecting water stress and chlorosis in crops by enabling zonal irrigation recommendations[16].

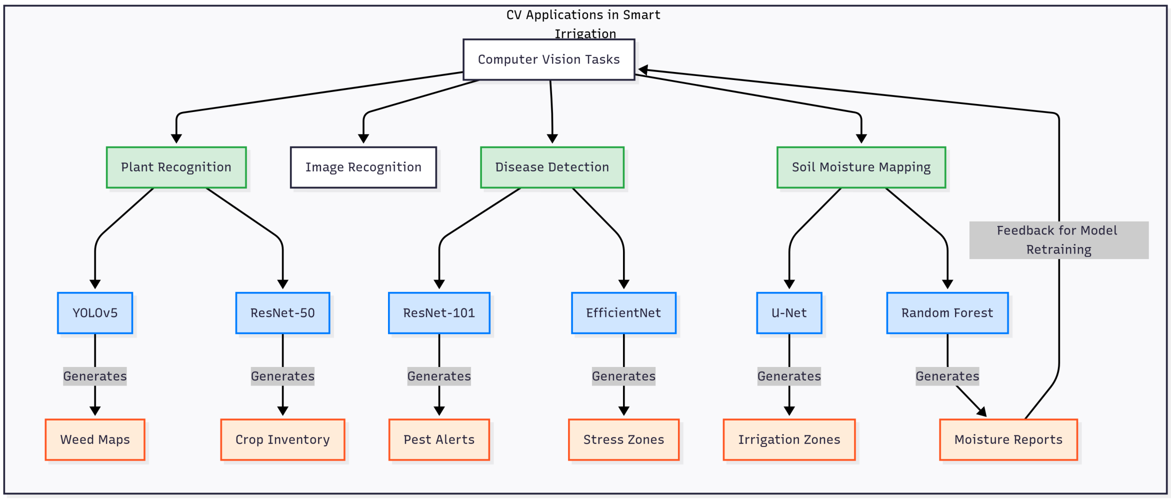

Figure 4. Computer vision applications in smart irrigation

4.4. Benefits of IoT and Computer Vision in Irrigation

The combined deployment of IoT and CV technologies yields multifaceted benefits. Precision irrigation systems utilizing these technologies have demonstrated water savings between 30% to 85%, while improving yield quality and quantity by 15% to 38% across different crops. Automated systems reduce energy consumption by facilitating low-pressure delivery methods (e.g., drip or micro-sprinklers), cutting energy usage by up to 25%.

Real-time monitoring and early detection of plant stress via IoT and CV reduces crop losses, enhancing food security. These systems also enable labor efficiency by automating repetitive monitoring tasks, with some studies reporting reductions in manual labor by 50–80%.

Integrated IoT frameworks, paired with cloud analytics and decision-support tools, enhance precision and scalability. Farmers can integrate multiple data streams—such as weather forecasts, evapotranspiration rates, and soil maps—for proactive intervention, reducing reliance on reactive methods. This holistic integration supports sustainable farming by reducing environmental impact, optimizing input usage, and enabling adaptive management under varying climate conditions.

Overall, IoT and computer vision technologies are pivotal to the digital transformation of agriculture. Their integration into irrigation management not only enhances productivity and profitability but also contributes significantly to the goals of resource conservation and climate-resilient agriculture.

5. Basic Steps of an IoT and Computer Vision Integrated Smart Irrigation System

5.1. Data Collection

IoT sensors deployed across the field collect real-time data on soil moisture, temperature, humidity, and rainfall. These sensors transmit data wirelessly to a central control unit or cloud platform.

Computer vision systems capture images of crops to monitor growth, detect pests, and assess plant health. Drones and satellite imagery provide aerial views and large-scale monitoring, while embedded soil sensors offer depth-specific moisture readings.

IoT weather stations enhance context by tracking temperature, humidity, and rainfall, aiding in the prediction of irrigation needs. Additionally, mobile applications allow farmers to input field data and receive alerts or recommendations from the system.

5.2. Error and Fault Detection

Anomalies in sensor readings—such as sudden spikes or drops—are flagged for potential malfunctions. Cross-verification among sensors helps identify discrepancies.

Threshold alarms trigger alerts when parameters exceed expected limits. Regular checks ensure the accuracy of camera systems, image recognition, and sensor calibration.

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Machine learning techniques are used to detect patterns indicating sensor faults or data inconsistencies. Backup systems (e.g., redundant sensors, power supplies) ensure reliability. Manual checks and user feedback further strengthen the system's error detection capabilities.

5.3. Data Processing

Raw sensor and image data undergo preprocessing (e.g., noise removal, normalization) before analysis. Data fusion integrates inputs from multiple sources to provide a comprehensive view of field conditions.

Advanced analytics and machine learning models predict crop water needs, optimize irrigation timing, and detect anomalies. A feedback loop continuously refines decisions based on real-time and historical data.

Results are visualized via dashboards and reports for farmer interpretation. Processed data is archived in local or cloud-based databases for future reference.

5.4. Wireless Communication

Wireless technologies enable seamless connectivity between sensors, cameras, control units, and cloud platforms. Common protocols include Wi-Fi, Zigbee, LoRaWAN, Bluetooth, and cellular networks.

Images and sensor data are transmitted to central processing units or cloud services for real-time analysis. Protocols like MQTT and HTTP ensure secure and efficient data transfer.

Mobile and web interfaces allow farmers to remotely monitor field conditions, receive alerts, and control irrigation systems. In remote areas, LPWAN technologies (e.g., LoRa, Sigfox) enable long-distance, low-power communication. Mesh networks improve reliability by enabling direct device-to-device communication.

Security features such as encryption, authentication, and access control are implemented to safeguard data integrity and confidentiality.

5.5. System Activation and Irrigation Control

Based on data analysis, the system determines optimal irrigation schedules considering soil conditions, crop type, weather forecasts, and growth stages.

The system activates irrigation devices—pumps, valves, and sprinklers—automatically or via remote control. It adjusts water application dynamically to reflect changing field conditions.

Real-time monitoring ensures that irrigation is effective and adaptive. Energy efficiency is enhanced through solar-powered components and optimization based on energy tariffs.

Integration with broader water management systems allows for region-wide water conservation strategies, contributing to sustainable agriculture.

6. Cost Efficiency of the Irrigation System

Achieving cost efficiency in an IoT and computer vision-enabled smart irrigation system requires strategic optimization of hardware, software, communication, and operational practices. The goal is to maximize agricultural value while minimizing the total cost of ownership. Key strategies for ensuring cost-effectiveness include:

- **Low-Cost and Energy-Efficient Hardware:** Selection of inexpensive, energy-efficient components such as soil moisture, temperature, and humidity sensors, along with low-power microcontrollers (e.g., ESP32, Arduino) and computer vision cameras with power-saving modes, significantly reduces hardware and energy expenses.
- **Open-Source Software:** Leveraging open-source platforms for control logic, data processing, and analytics eliminates licensing fees and lowers software development costs. Libraries like TensorFlow Lite, OpenCV, and Node-RED can support advanced functionalities at minimal expense.

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- **Cloud-Based Services:** Utilizing cloud infrastructure for data storage and processing offers scalable, pay-as-you-go pricing models. This avoids large upfront infrastructure investments while enabling flexible data management and system expansion.
- **Optimized Communication Protocols:** Employing low-bandwidth, long-range wireless technologies such as LoRaWAN or Zigbee minimizes data transmission costs, particularly in rural or large-scale deployments with limited cellular coverage.
- **Data Compression and Aggregation:** Aggregating and compressing sensor and image data before transmission conserves bandwidth and reduces cloud storage requirements. Techniques such as local filtering and threshold-based reporting can significantly lower recurring operational costs.
- **Edge Computing:** Processing data locally on IoT nodes or edge gateways reduces cloud dependency and network latency. This approach not only lowers data transmission costs but also enables faster decision-making in real-time irrigation control.
- **Modular and Scalable Architecture:** Designing systems with modular components allows for incremental expansion as needed. This ensures that investment scales with demand, avoiding unnecessary upfront expenditure.
- **Lifecycle Cost Consideration:** A comprehensive lifecycle cost analysis—including procurement, installation, maintenance, and eventual replacement—enables more informed budgeting and investment strategies that prioritize long-term savings over short-term gains.
- **Return on Investment (ROI) Evaluation:** Conducting ROI analyses that account for water savings, enhanced crop yield, labor reduction, and decreased input costs helps to justify the initial investment. Quantifiable economic benefits can support farmer adoption and policy support.

In summary, a well-planned combination of affordable technology, efficient system design, and strategic data management practices can make smart irrigation systems both economically viable and technically sustainable. Table 6 presents a comparison of the return on investment (ROI) for selected smart irrigation systems, showing that systems with low initial costs can still yield substantial water savings and productivity improvements.

Table 6. ROI Summary of Selected Smart Irrigation Systems.

Study	Initial Cost ($)	Water Savings (%)	Yield Increase (%)	ROI Estimate
Hazic et al. (2022)	46	85	23	High
Vijayaraja et al. (2022)	100–150	48	20	Moderate
Senthil Vadivu et al. (2023)	200–300	40	38	Moderate
Patil et al. (2023)	50–100	80	15–25	High

Comparative Lifecycle Costing and ROI in Emerging Economies: Recent research highlights that lifecycle cost analyses are critical for assessing the true economic viability of smart irrigation systems, especially in developing regions. For instance, Das et al. (2023) evaluated drip irrigation with sensor automation in Bangladesh and found that initial costs were offset within 2.5 years due to a 42% reduction in water usage and a 30% increase in yield[8]. Similarly, Afolayan et al. (2024) conducted a cost-benefit analysis of solar-powered IoT irrigation in sub-Saharan Africa, reporting a 1.9 benefit-cost ratio and a 3-year payback period, underscoring the long-term affordability and sustainability in resource-limited contexts [1]. These studies suggest that, despite higher upfront investment, smart irrigation delivers considerable ROI when scaled and maintained appropriately.

7. Techniques Used in Smart Irrigation Systems

Smart irrigation systems leverage a range of technologies and platforms, each offering distinct capabilities in terms of cost, scalability, and system complexity. The following are widely adopted techniques in the development and deployment of such systems:

Arduino-Based Systems

Due to their cost-effectiveness and ease of use, Arduino boards are widely adopted for prototyping and teaching purposes. These boards enable basic sensor integration and control functions, making them ideal for entry-level smart irrigation projects. However, they may fall short in handling advanced features such as large-scale data processing, cloud integration, or real-time analytics. This limitation affects their suitability for commercial-scale deployments.

Fuzzy Logic Controllers

Fuzzy logic offers a rule-based control mechanism that mimics human reasoning in decision-making processes. When embedded within Arduino or similar platforms, fuzzy logic controllers enable adaptive irrigation decisions based on imprecise or variable input parameters (e.g., soil moisture levels or weather forecasts). While this approach enhances flexibility and responsiveness, it requires careful tuning of membership functions and rule sets, demanding greater computational resources and domain expertise.

NodeMCU and ESP8266 Modules

The NodeMCU platform, based on the ESP8266 Wi-Fi module, provides a cost-effective and IoT-ready solution for smart irrigation systems. It supports real-time wireless communication and direct cloud connectivity, enabling efficient data transmission and remote monitoring. Its built-in Wi-Fi capabilities make it particularly suitable for distributed systems that rely on wireless sensor networks and internet-based control interfaces.

FIWARE Framework

FIWARE is an open-source, standards-based platform that supports the development of scalable and interoperable smart applications, including agricultural solutions. It offers advanced functionalities such as context-aware data management, interoperability with IoT devices, and real-time analytics. While FIWARE is ideal for building comprehensive, city- or region-level irrigation solutions; its complexity and setup requirements may pose challenges for small-scale or resource-constrained deployments.

Wireless Sensor Networks (WSNs)

WSNs form the backbone of real-time environmental monitoring in smart irrigation systems. These networks consist of distributed sensor nodes that collect data on soil moisture, temperature, humidity, and other agronomic variables. WSNs offer high scalability, energy efficiency, and flexible deployment options across diverse terrains. However, their cost-effectiveness depends on several factors, including the density of sensor deployment, communication range, energy consumption, and maintenance requirements.

8. Gaps Identified

Despite the growing adoption of IoT and machine learning in smart irrigation systems, several challenges persist that hinder the development of effective and scalable solutions for sustainable agriculture.

One of the foremost challenges lies in addressing the increasing demand for food and industrial crops, such as cotton and rubber, while minimizing environmental impacts. Meeting global food shortages and industrial demands necessitates the cultivation of high-income crops, which must be balanced with the use of sustainable practices to prevent soil degradation and contamination [13].

At the same time, the agricultural sector faces significant constraints, including a shrinking labor force, a reduction in arable land, the depletion of water resources, and the adverse effects of climate change. Rapid urbanization and demographic shifts, particularly population aging and rural-to-urban migration, further exacerbate these issues by diminishing the availability of skilled labor in rural farming communities.

While IoT technologies offer promising applications in smart irrigation and precision agriculture, several technical and practical aspects remain underdeveloped. These include the need for:

- **Cost-effectiveness:** Many current systems are prohibitively expensive for smallholder or resource-limited farmers.
- **Robust design and durability:** Field-deployed devices must withstand harsh environmental conditions and function reliably over time.
- **Portability and autonomy:** Systems need to be lightweight, self-powered, and easily deployable across different farming landscapes.
- **Low maintenance:** Maintenance-free or low-maintenance systems are essential to reduce operational burdens on farmers.
- **Reliability:** Accurate and uninterrupted data collection and decision-making are vital for trust and effectiveness.

To realize the full potential of smart irrigation, integrated systems must be designed to leverage artificial intelligence, big data analytics, and cloud computing. Future systems are expected to incorporate a wide range of equipment and technologies, enabling end-to-end agricultural management—from planting to predictive yield forecasting.

Emerging technologies such as agricultural robotics, AI-driven decision support systems, and cloud-connected data platforms hold the potential to revolutionize irrigation practices. However, their adoption is contingent upon addressing the accessibility, affordability, and ease-of-use concerns for farmers and agricultural stakeholders.

A key opportunity lies in the convergence of machine learning-based forecasting models with user-friendly, portable software tools. Such tools can enhance water-use efficiency by improving the accuracy of irrigation demand predictions, aligning irrigation volume and timing with plant-specific requirements, and dynamically adjusting for environmental water loss.

Improving these aspects can contribute to higher crop yields with reduced water consumption, ultimately supporting the goal of sustainable agriculture. As the underlying technologies mature, smarter and more adaptive irrigation models can significantly reduce the cognitive and physical burden on farmers, empowering them to make informed, data-driven decisions with minimal intervention.

Table 7. Functional Layers of IoT-Based Smart Irrigation Architecture.

Layer	Technologies	Functions
Things	Sensors, actuators	Collects soil moisture, temperature; controls irrigation devices
Edge	Microcontrollers, gateways	Local data processing, real-time decision-making
Communication	LoRa, MQTT, Wi-Fi	Transmits data between devices and cloud
Cloud	Databases, analytics platforms	Stores data, performs analytics, provides user interfaces

9. General Architecture of IoT-Based Irrigation Systems

The architecture of IoT-based smart irrigation systems is structured into four layers: Things, Edge, Communication, and Cloud (Figure 5). Table 7 summarizes the functions and technologies of each layer. The Things layer includes sensors (e.g., soil moisture, temperature) and actuators (e.g., pumps, valves) for environmental monitoring and control. The Edge layer processes data locally to reduce latency, while the Communication layer employs protocols like LoRa and MQTT for efficient data

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transfer. The Cloud layer supports scalable storage, advanced analytics, and farmer interfaces. This modular design ensures scalability and interoperability, with variations like three-tiered models used in smaller deployments.

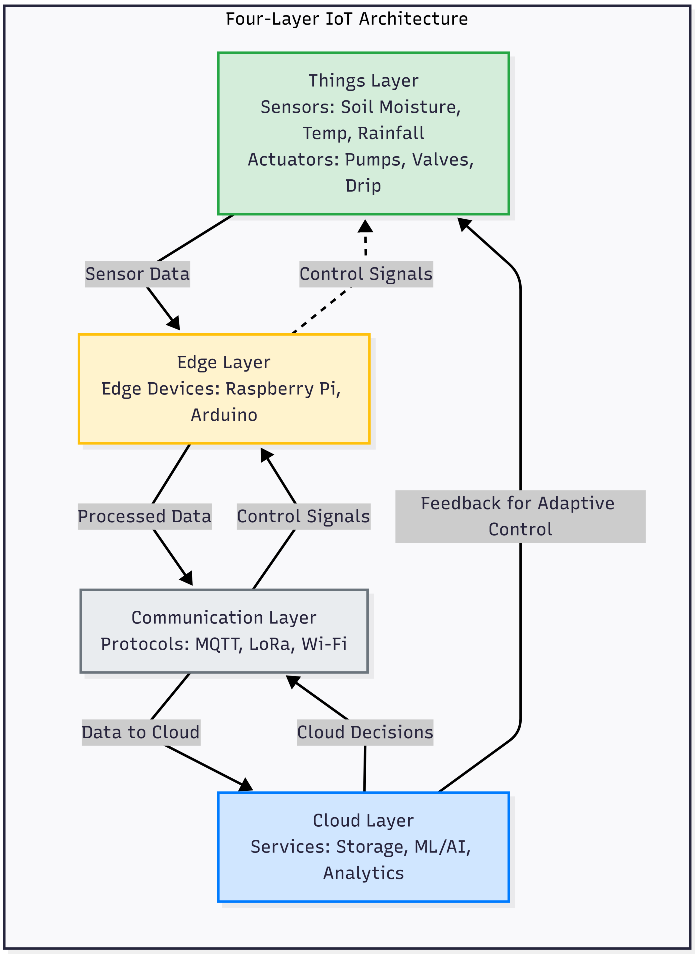

Figure 5. Four-layer IoT architecture for smart irrigation systems

Four-Layer Model

In addition to the three-layer model, some architectures introduce an intermediate **service layer**, often positioned between the network and application layers. This layer leverages fog or cloud computing to store, process, and analyze large volumes of sensor data, enabling low-latency responses and intelligent decision-making [31]. As shown in Figure 5, the four-layer IoT architecture for smart irrigation systems consists of the Things, Edge, Communication, and Cloud layers, enabling real-time sensing, control, and analytics.

A widely cited example of such a layered architecture is the four-layer model proposed by Ferrández-Pastor et al. [14], which includes:

- **Things Layer:** Comprising the physical sensors and actuators embedded in the field.
- **Edge Layer:** Responsible for preliminary data processing and control operations near the source.
- **Communication Layer:** Facilitates reliable data exchange between edge devices and cloud systems.
- **Cloud Layer:** Offers scalable storage, advanced analytics, and remote management capabilities.

Tiered Functional Architecture

Several studies adopt a three-tiered functional model comprising:

- **Lower Tier:** Sensor nodes and actuators directly interact with the agricultural environment.

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- **Intermediate Tier:** Gateways or edge devices handle data aggregation and local decision-making.
- **Upper Tier:** Cloud infrastructure supports high-level analytics, application interfaces, and long-term data storage [4].

These architectures may vary in complexity depending on the scale of deployment, specific application requirements, and resource constraints. However, the fundamental principles of layered abstraction, modularity, and interoperability remain consistent across implementations.

10. Future Direction

The future of smart irrigation lies in the seamless integration of IoT and computer vision technologies to enhance accuracy, operational efficiency, and cost-effectiveness. Several research and development directions can guide the evolution of next-generation smart irrigation systems [22,25,26,38,45]. Table 8 outlines key emerging technologies anticipated to shape the future of smart irrigation, highlighting their potential benefits, technical hurdles, and example deployments.

Table 8. Emerging Technologies for Future Smart Irrigation.

Technology	Potential Impact	Challenges	Example Applications
Edge Computing	Enables real-time decision-making; reduces latency and cloud dependency	High initial hardware complexity; limited processing power on edge devices	LoRa-based edge irrigation controllers (e.g., Puig et al., 2022)
Energy Harvesting	Supports autonomous operation in off-grid or rural areas	Efficiency and durability of energy systems under harsh conditions	Solar-powered NodeMCU systems (e.g., Vijayaraja et al., 2022)
AI-Driven Forecasting	Improves irrigation accuracy via predictive models; enhances crop yield	Requires large datasets and model interpretability	Decision tree and neural network systems (e.g., Alphonse et al., 2023; Bakare, 2023)
Flexible/Printed Sensors	Reduces sensor cost; enables deployment on diverse surfaces (e.g., leaves, soil)	Durability and accuracy under environmental stress	Early-stage research in plant-wearable moisture sensors
Blockchain for Data Integrity	Secures data sharing and traceability in precision farming ecosystems	Scalability, energy use, and technical complexity	Pilot projects in agricultural supply chains and IoT trust layers
Interoperable IoT Standards	Promotes integration with existing farm management platforms	Lack of unified standards; vendor lock-in risks	FIWARE-based frameworks enabling modular sensor integration

Note: These technologies represent cutting-edge research and pilot-stage deployments, with varying degrees of maturity.

10.1. Enhanced Sensor–Vision Integration

A key future trend is the tighter integration of IoT sensors and computer vision systems. By combining environmental sensor data (e.g., soil moisture, temperature) with real-time image analysis, systems can generate more precise insights into crop health, disease symptoms, and water stress levels. This fusion of multimodal data enables the generation of optimized irrigation schedules tailored to crop-specific and location-specific needs.

10.2. Edge Computing for Real-Time Decision Making

The adoption of edge computing will reduce latency and minimize reliance on continuous cloud connectivity. Localized data processing on IoT nodes or edge servers can support faster decision-

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making, reduce bandwidth consumption, and ensure uninterrupted system performance in remote agricultural environments. Edge analytics also enhances privacy and contributes to cost-effective, scalable system architectures.

10.3. Energy Harvesting and Low-Power Design

To improve system sustainability, future research should explore energy harvesting techniques such as solar, kinetic, or thermal energy to power field devices. When paired with low-power algorithms and energy-efficient hardware, these solutions can extend device lifespan, reduce maintenance frequency, and decrease dependency on external power sources or frequent battery replacements.

10.4. Development of Cost-Effective Sensors

Innovation in low-cost sensing technologies remains critical. Research should focus on the development of affordable, durable sensors capable of monitoring soil nutrients, moisture, ambient climate, and crop conditions. Technologies such as printed electronics and flexible sensors offer promising alternatives that can reduce manufacturing and deployment costs without compromising performance.

10.5. Privacy and Data Security

As data collection intensifies, ensuring data privacy and system security becomes increasingly important. Future systems must incorporate robust mechanisms for access control, authentication, and end-to-end encryption to protect sensitive environmental and agricultural data. Strengthening cybersecurity measures will be essential to build user trust and regulatory compliance.

10.6. Localization and Adaptive Systems

Smart irrigation systems must be tailored to accommodate diverse agro-climatic zones, soil types, and crop varieties. Localization techniques that incorporate local weather data, agronomic practices, and forecast models will enable the design of adaptive irrigation strategies that are both efficient and resource-conscious. Flexibility in system behavior across regions will ensure higher adoption rates and greater environmental relevance.

10.7. Interoperability and Open Standards

To promote long-term viability, smart irrigation solutions should adhere to open standards and interoperable protocols. This will facilitate seamless integration with other farm management systems and IoT ecosystems, enabling modular upgrades and vendor-independent expansion. Open-source development and community-driven innovation can further accelerate progress and reduce barriers to adoption.

10.8. Field Testing and Participatory Design

Finally, large-scale field trials and pilot studies across diverse agricultural contexts are crucial for validating technical performance, scalability, and economic impact. Engaging farmers and end-users in the design, testing, and refinement process ensures that systems address real-world challenges and are aligned with user expectations. Feedback loops from field deployments will drive iterative improvements and facilitate technology transfer to commercial agriculture.

11. Conclusions

As technology continues to evolve rapidly, modern agricultural practices are increasingly driven by innovation. Smart irrigation, driven by the integration of IoT and computer vision technologies, offers significant potential to optimize water usage, improve crop yields, and support sustainable farming practices.

Modern farmers increasingly rely on sensor-based systems to monitor crop health, environmental conditions, and resource utilization. These systems not only help in conserving water and energy but also reduce the environmental footprint of agricultural activities. IoT technologies have facilitated the automation of various agricultural processes, thereby enhancing overall productivity and efficiency. However, despite their proven benefits, the widespread adoption and full exploitation of these technologies remain limited, particularly in resource-constrained settings.

Water scarcity, including stress, shortages, and crises, continues to pose a major challenge in agricultural regions globally. This has intensified the focus on efficient water resource management. Smart irrigation systems, which leverage IoT for automated control and real-time monitoring, are becoming essential tools in addressing these challenges. These systems enable farmers to make informed decisions based on accurate, real-time data, thereby reducing waste and improving output.

The role of wireless sensor networks (WSNs), IoT-enabled devices, and computer vision technologies has been pivotal in transforming traditional irrigation practices. IoT reduces the overall cost of monitoring and control infrastructure, while computer vision enables precision irrigation, intelligent resource allocation, and automation of labor-intensive tasks, thereby reducing dependency on manual labor.

In conclusion, the integration of advanced technologies such as IoT and computer vision holds the key to enabling a shift toward sustainable, data-centric, and highly efficient farming practices.

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Abbreviations

Abbreviation	Definition
IoT	Internet of Things
GSM	Global System for Mobile Communications
LoRa	Long Range
NodeMCU	Node Microcontroller Unit
ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
NDVI	Normalized Difference Vegetation Index
YOLO	You Only Look Once
UAV	Unmanned Aerial Vehicle
CNN	Convolutional Neural Network

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