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REVIEW

Internet of Things in Sustainable Agriculture Systems

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ABSTRACT

The agriculture industry has evolved toward intelligent, data-driven processes due to the growing need for food worldwide, environmental sustainability, and effective resource use. A thorough analysis of smart agriculture as a game-changing element of the industry 4.0 revolution is provided in this study, with a focus on the incorporation of Internet of Things (IoT)-based technologies for sustainable farming. To optimize agricultural processes including irrigation, crop health monitoring, climate and weather tracking, animal management, and disease detection, it investigates the functions and uses of smart sensors and IoT devices. The study demonstrates how smart agriculture may meet important issues like food shortages, environmental degradation, and wasteful resource use by combining the latest scientific developments with practical applications. The study also covers the enabling technologies that facilitate real-time agricultural monitoring and decision-making, including artificial intelligence (AI), cloud computing, and cellular networks. It ends by outlining the main obstacles, existing constraints, and potential avenues for further study in the development of robust, technologically advanced agricultural systems.

Keywords: Internet of things, Sensors, Sustainable transportation, Machine learning, Artificial intelligence

1. Introduction

Smart agriculture is an industry 4.0 green revolution approach for sustainable and efficient agricultural future [1–3]. This concept leverages on smart technologies to open new opportunities for sustainable agricultural systems and addressing ecosystem degradation, resource scarcity and food security [4–6]. Agriculture sector has long been seen as a bedrock of economy in terms of food security, poverty alleviation, and raw materials [7–9]. This sector contributes significantly to food security, particularly in emerg-

ing nations where it serves as a source of livelihood and employment [10]. As reported in [11], growing population and increasing demand for nutritious food further increases the burden of agricultural systems.

For variety of reasons, countries have begun to shift towards sustainable agriculture to enhance food production and preserve environmental integrity, with special emphasis on smart agricultural systems. Sustainable agriculture is now part of several sustainable development goals and targets aimed at promoting biodiversity and ecosystem health, climate-smart agriculture, and improving nutrition and food

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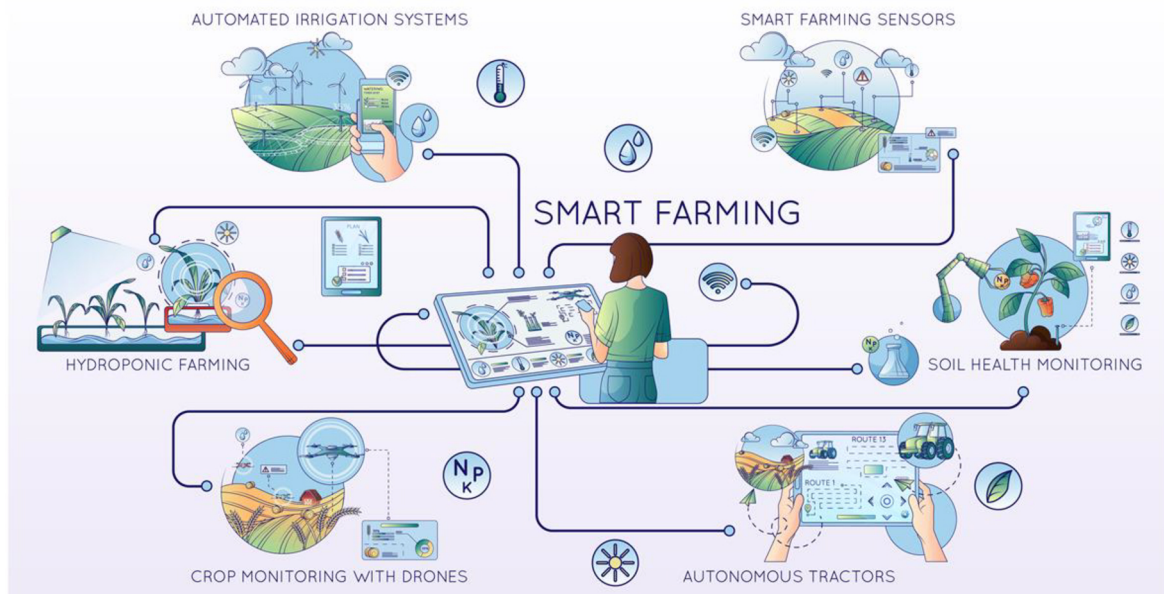


Fig. 1. Application of IoT in smart farming adopted in [1].

availability, income stability and economic resilience [12]. The United Nation's (UN's) focus on sustainability, efficiency, and resilience to address problems of climate change, resource depletion, and food scarcity.

In this context, smart innovations—particularly those powered by the IoT—present transformative opportunities for the agricultural sector. IoT is experiencing significant growth in the agricultural sector, driven by the increasing demand for agricultural products, advancements in technology and the need for an efficient farming system. In addition, the growth of IoT in agriculture market has been significant, and is further anticipated to grow at a 9.5% within the next decade, resulting in a market value of USD71.75 billion in 2032 [13].

This expanding trend emphasizes how urgently a thorough analysis of smart technologies in agriculture is needed. Even though several IoT-based technologies and solutions have been created and implemented, there is still a dearth of comprehensive information connecting these advancements to sustainable farming methods. By methodically examining contemporary applications, technologies, and innovations—such as smart irrigation systems [14, 15], livestock monitoring [19], crop health monitoring [25], soil nutrient tracking [46], meteorological and climate monitoring [36], pest and disease detection [40], nutrient management [47], and agricultural drones [61]—this review seeks to close that gap.

Smarter, data-driven decisions are being made possible by these technologies, which are changing conventional farming methods. At the heart of this

change are IoT-powered innovations like drone-based monitoring, hydroponic farming, automated irrigation, and autonomous tractors, as seen in Fig. 1.

Thus, this review's goals are threefold: (1) to assess the state and uses of smart technologies and the Internet of Things (IoT) in agriculture; (2) to evaluate important technologies like communication networks, smart sensors, IoT and (3) to determine the difficulties, and future research paths for sustainable smart agriculture systems.

2. Smart technologies in agriculture

The integration of digital tools including sensors, IoT, data analytics, and automation to improve farming productivity, sustainability, and efficiency is referred to as “smart technologies” in the agricultural industry. These technologies make it possible to precisely monitor and regulate agricultural characteristics such as temperature, crop health, livestock conditions, and soil moisture. Smart agricultural technologies decrease resource waste, increase yields, and tackle issues like food security and climate change by gathering data in real-time and enabling informed decision-making.

2.1. Smart sensors in agriculture

Smart sensors in agriculture are crucial tools for real-time monitoring and automation of farming activities. Several sensor types have been used in agricultural systems to monitor and control

Table 1. Categories of sensors currently used for agriculture.

Sensor type	Purpose	Application domain	Reference
Passive infrared (PIR) motion sensors	To monitor movement (e.g., of pests or intruders) in grain storage facilities or barns.	Storage of agricultural produce	[38]
Digital Humidity and Temperature (DHT) sensors	Used by farmers for planning, planting and harvesting and monitoring crops' temperature and humidity levels	Livestock management and climate-weather monitoring	[14, 17, 18, 31]
Nutrient sensors	To measure soil nutrients such as nitrogen and phosphorus	Nutrient monitoring	[46]
Pest and disease detection sensors (for example, Red, Green, Blue (RGB), Multispectral, Hyperspectral, Thermal)	To detect early signs of pest infestations or diseases in crops.	Pest and disease detection	[65, 77]
Crop growth sensors (LIDAR (Light Detection and Ranging), ultrasonic sensors, optical sensor)	Used to monitor plant growth parameters such as height and biomass	Crop management	[27, 65]
Gas sensor	To detect toxic gases in livestock including poultry system.	Livestock monitoring	[124, 125]
Flow sensors, evapotranspiration (ET) sensors, wind sensors and Rain sensors	Used to monitor water content in the soil	Irrigation monitoring	[14]
Drone-mounted sensors	Unmanned Aerial Vehicles (UAVs) equipped with various sensors, multi-spectral, thermal, and LiDAR are used for real-time data collection in agriculture	Gasoline vapor (VOCs), CO sensors, O2 sensors, NOX sensors and particle Matter (PM) sensors	[45]
Soil sensors	Used to measure soil parameters such as moisture PH, and nutrient levels.	Remote sensing monitoring	[14, 18]
Tractor –mounted sensors (Global Positioning System (GPS), inclinometers and rotary angle, and telematics)	These sensors are installed on tractors to determine precise location, monitor tractor's angle, and position, to provide feedback for auto-steering systems and provide real-time data on the tractor's status including location, fuel consumption, and operational efficiency.	Farm machinery management	[20]

physical variables such as temperature, humidity, light moisture and toxic gases [26]. Smart sensors are semiconductor devices that utilize advanced algorithms to detect and monitor changes in physical parameters including temperature, humidity, soil moisture, and light intensity. These sensors are integrating into various application domains, particularly in agriculture to improve farming operations and productivity. Commonly used sensors used in agriculture have been reviewed and presented in Table 1.

2.2. Internet of things applications in agriculture

The IoT has fostered agriculture efficiency, productivity, and sustainability. The integration of smart sensors, IoT technologies, and data analytics allows for remote monitoring of farmer activities which helps to enhance resource management and increases crop yield and quality. This section examines some of the IoT applications in smart agriculture with special on (1) smart irrigation, (2) livestock monitoring, (3) crop health monitoring, (4) climate-weather monitoring, (5) pest and disease detection, (6) nutrient management, (7) greenhouse monitoring and (8) agricultural drones.

2.2.1. Smart irrigation system

Smart irrigation leverages IoT to automate and optimize water usage in plants/crops [14]. This system reduces waste and conserves water while ensuring crops receive the optimal amount of water, and the soil moisture level is suitable for crop growth [15]. This system can automatically adjust watering schedules based on real-time data [16], to minimize the risk of overwatering and maintain optimal soil moisture levels [17], leading to improved crop growth and crop yield [18]. Additionally, smart irrigation can enhance crop productivity, increase food availability, and crop yield [10]. Software cloud-based platforms and emerging communication technologies such as 5G cellular networks and Artificial Intelligence (AI) are currently being deployed in irrigation systems to improve remote monitoring and real-time data analytics [16].

Several researchers have developed cutting-edge smart irrigation systems in the quest for precision agriculture, which successfully automate water management by fusing sensor technologies, micro-controllers, and cloud platforms. By intelligently reacting to current soil and environmental conditions, these systems aim to maximize water use. A solid

basis was established by Bounnady et al. [14], who created a real-time soil moisture monitoring system using the ESP8266 microcontroller. A collection of sensors was used in the setup: a water flow sensor to assess irrigation usage, a DHT11 for ambient temperature and humidity, and a soil moisture sensor to detect hydration levels. The Thing Speak cloud received the collected data, allowing farmers to access it remotely. A relay-controlled solenoid valve operated to irrigate the soil when moisture levels fell below threshold levels, which was a unique feature of their system. The technology ensured sustainability and efficiency by cutting off the feed as soon as the ideal moisture level was restored.

In a similar vein, Kumar et al. [15] presented an automated irrigation system that uses an embedded microprocessor and soil moisture sensors to assess the situation and start watering. However, by more closely integrating the sensors with the system's decision-making core, their method placed more emphasis on responsive water distribution than Bounnady et al. An early attempt at incorporating Internet of Things (IoT) concepts into field-level water management was demonstrated by the ability for farmers to remotely monitor and control the system using personal computers (PCs) or mobile devices. This idea was extended by Bakare et al. [16] using a wider range of sensors, such as a Light Dependent Resistor (LDR), which accounts for light intensity in addition to temperature, humidity, and soil moisture. A Peripheral Interface Controller 18F4620 (PIC18F4620) microcontroller, which was coded in C++ within the MPLAB IDE, handled the decision-making, providing a strong processing foundation for the system. Local wireless connection was made possible by a Bluetooth module, and users may manually override or monitor processes from a Windows interface using a proprietary Visual Basic. Net (VB.NET) application. This system combined user-controlled flexibility with automated triggers, emphasizing versatility.

Ihendinihu and Inyama [17] devised a more simplified technique, utilizing an Arduino microcontroller and a DHT11 sensor to create a simple yet efficient device. When soil moisture levels decrease, the system automatically starts watering using a relay-activated pump. Through its interaction with the ThingSpeak platform and GSM/Wi-Fi modules, farmers were able to access real-time data visualizations on desktop or mobile devices. The system was quite useful for smallholder farms despite its simplicity because of its effective operation and remote monitoring features. Abdikadir et al. [18] developed a comprehensive system that integrated sensor data and external weather inputs, furthering the concept of smart irrigation. The system used Raspberry Pi as the main computing de-

vice to gather data from DHT11 and Soil Moisture Sensor v2.0 units. Cloud integration and analytics were handled using the Favoriot platform, while data flow and control logic were managed by Node-RED. By connecting real-time soil data with more general climatic trends, this hybrid method gave the system a higher degree of intelligence and adaptability and enabled it to make sophisticated irrigation decisions.

2.2.2. Livestock monitoring

Livestock monitoring refers to livestock tracking based on connected devices like sensors [19], collars, and wearable tags [20] to gather data on animal health, location, and behaviour [21]. This system uses smart sensors to monitor vital signs such as heart rate, body temperature, and control environmental parameters within livestock facilities [22]. These systems can regulate temperature, humidity levels, and optimize animal diets. Currently, various emerging technologies used in livestock monitoring systems include wearable sensors, blockchain, cloud computing, and 5G cellular networks to improve livestock health [23], illness detection, preventive healthcare, nutrition, and enhance reproductive performance [24].

A hybrid convolutional neural networks and gated recurrent unit (CNN-GRU) model was presented for categorizing cow behavior using an inventive combination of wearable sensor data and deep learning. Using accelerometers, magnetometers, and gyroscopes, data was collected from dairy cows and converted into time-frequency characteristics using the Short-Time Fourier Transform (STFT). The CNN-GRU network achieved 91.40% accuracy in multi-class categorization of behaviors like walking, grazing, lying, and ruminating thanks to this rich dataset, which enabled the network to capture both spatial and temporal dynamics [19].

An end-to-end IoT system that uses Long Range Wide Area Network (LoRaWAN) for low-power, long-range livestock tracking, with an emphasis on infrastructure, was also proposed. With a battery life of more than six months, the hardware design included motion, temperature, and global positioning system (GPS) sensors to relay data up to 1.5 kilometers. Real-time tracking of animal locations and health indicators was made possible using a web-based interface. This system demonstrated how connectivity solutions may provide useful and scalable livestock monitoring by enabling the detection of possible abnormalities like theft, boundary violations, or health problems [20].

Health-focused monitoring was further investigated, particularly for the early detection of digital dermatitis (DD), a painful hoof condition in dairy cows. Using machine learning on behavioral sensor

data, models were developed to identify and forecast DD. The model achieved 79.00% accuracy on the day of symptom onset and maintained 64.00% accuracy two days beforehand [21].

A deep learning system for autonomous video-based behavior analysis was created, moving the emphasis from sensors to visual intelligence. With an overall accuracy of 81.2% in cow identification, the model, trained on farm footage, was able to identify individual cows and detect actions like drinking (84.4%) and grazing (94.4%). This passive video method provides a non-intrusive substitute for wearable technology, particularly beneficial in settings with open grazing or large herds [22].

A non-invasive visual recognition method using deep metric learning and CNNs was proposed to enhance animal identification. By analyzing the distinctive coat patterns of Holstein-Friesian cattle, the technique identified individuals with 93.80% accuracy. This strategy supports welfare tracking and traceability, especially in contexts where wearables or tagging are impractical [23].

Behavior classification under complex farm conditions was advanced using a Convolutional Neural Network Bidirectional Long Short-Term Memory (CNN-Bi-LSTM) hybrid model. By analyzing accelerometer data, the model was able to capture both temporal and spatial dependencies, making it ideal for settings influenced by diverse dynamic elements. Even under real-world conditions, the model reliably identified behavioral patterns [24].

2.2.3. Crop health monitoring

The systematic assessment of crop condition through their growth cycle can be enhanced with IoT [31]. Various technologies including sensors, GPS, satellite imagery, and machine learning can be used to provide real-time information on crop health, soil moisture, nutrient deficiencies, leaf temperature, pest infestations, chlorophyll level, and environmental parameters [25–30]. This system allows farmers to optimize resources while ensuring that crops receive proper nutrients and water for improved crop yields [27–33]. In addition, this system can track soil health indicators such as nutrient levels and microbial activity to improve soil fertility and biodiversity [28, 30–32].

Researchers are advancing plant health monitoring in modern agriculture by combining cutting-edge sensing technologies with artificial intelligence, whether in open fields or vertical farms. From long-term satellite-based field mapping to real-time stress detection, the objective is always the same: identify and address plant distress before it impairs yield.

In a groundbreaking effort tailored for controlled-environment agriculture and even space farming, a small hyperspectral imaging device that combines fluorescence and reflectance imaging in the VNIR spectrum was used to identify drought stress in lettuce through a line-scan camera and Light Emitting Diode (LED) lighting, recording fine-grained spectral data. With machine learning classifiers, early stress was identified with over 90% accuracy—within four days, long before symptoms were apparent—demonstrating the critical role of spectral analysis in proactive crop management, particularly in space-constrained environments [26].

A more comprehensive approach applied to Fully Connected Neural Networks (FCNN) alongside satellite-derived NDVI (Normalized Difference Vegetation Index) to distinguish between stressed and healthy crops, especially those affected by rust. This integration of deep learning and vegetation indicators enabled high-precision agricultural monitoring at scale, achieving a classification accuracy of 97.80% [25].

To address challenges in vertical farming, a multi-spectral LED (light emitting diode) system emitting UVA and NIR (near infrared) light was developed to monitor plant health using a UV-NDVI (Ultraviolet-Normalized Difference Vegetation Index metric). This real-time, reflectance-based system allowed vertical farm operators to detect and respond to early stress signals efficiently within controlled environments [27].

To deepen the understanding of plant physiology, a network of flexible biosensors was designed to measure stem development, vapor pressure deficit, and key plant hormones such as salicylic acid and ethylene. These sensors, mounted directly on live plants, provided continuous insights into internal stress responses, bridging the gap between biophysics and precision agriculture [28].

From a remote sensing perspective, a system utilizing high-resolution satellite imagery, such as PlanetScope, and APIs was created to generate seasonal field maps based on vegetation indices. These maps facilitated germplasm selection and disease resistance breeding, contributing to both real-time crop surveillance and long-term crop protection strategies [29].

At the field level, an IoT-based mobile application integrated soil moisture sensors, BMP280 temperature sensors, and cloud services like Google Firebase and Airtable. This tool delivered real-time environmental data and crop recommendations tailored to soil type and seasonal patterns, acting as both a monitoring solution and decision support system [30].

Another IoT monitoring system employed DHT11 and soil moisture sensors to collect and stream data, which was then analyzed using a convolutional neural network (CNN) to predict crop conditions, offering automated diagnostic capabilities beyond simple monitoring [31].

A scalable, multi-location crop monitoring system incorporated Linear Monolithic-35 (LM35) temperature sensors, soil moisture probes, and dual connectivity (Wireless Fidelity (Wi-Fi) and Global System for Mobile Communications (GSM)) for seamless data transmission. Cloud-based analytics transformed the collected data into actionable insights in real time [32].

Lastly, an AI-powered smart agriculture platform monitored temperature, moisture, soil pH, salinity, electrical conductivity, and macro-nutrients such as nitrogen, phosphorus, and potassium. Field trials on rice farms showed improved fertilizer management, irrigation, and disease prevention, driving smarter and more sustainable farming practices [33].

2.2.4. Climate and weather monitoring

Climate and weather can significantly affect crops through different mechanisms such as temperature changes, altered precipitation patterns, soil health issues, pest dynamics, and food security challenges. Due to climate changes, agricultural produce's quality and quantity may be affected. Hence, farmers may use sensors to collect various environmental data including temperature, humidity, soil moisture, and atmospheric pressure [34, 35]. IoT technology can help farmers identify potential weather risks on crops and allow them to take preventive measures to protect their crops [36]. With accurate weather forecasts and climate monitoring, farmers can implement timely interventions that improve crop growth and resilience against climate variability [37].

A series of complementary experiments covering sensor integration, machine learning, real-time forecasting, and data validation graphically highlight the synergy between contemporary agriculture and cutting-edge climate monitoring technologies. In addition to improving our knowledge of regional environmental trends, these empirical studies show how technology can revolutionize conventional farming methods into data-driven, intelligent systems. An Internet of Things-based weather monitoring system was developed specifically for Ghanaian farmers, laying the foundation for farmer-centric innovation. Temperature, humidity, and precipitation are tracked using Arduino-powered sensors, which send real-time data to a cloud server accessible via a mobile app. Automated notifications ensure that farmers are aware of adverse weather conditions, allowing for proactive

adjustments to planting, irrigation, and pest management plans [34].

Building on this framework, a model integrating Gated Recurrent Units (GRUs) was introduced to add predictive intelligence to field monitoring. This system analyzes soil moisture and nutrient levels while forecasting future weather events, enabling strategic rather than reactive decision-making [35]. A modular environmental control system was also designed for greenhouse environments, combining sensors, actuators, and cloud platforms to continuously regulate internal growing conditions and optimize productivity [36]. To enhance data reliability, another study applied Bayesian time-series models to validate sensor inputs, significantly reducing false readings and increasing confidence in automated systems [37].

Taken together, these systems highlight that achieving climate-smart agriculture requires more than just deploying sensors or algorithms—it necessitates an integrated ecosystem of reliable data acquisition [37], localized deployment [34], predictive modelling [35], and intelligent control mechanisms [36] that together transform farming from analog intuition to digital precision.

2.2.5. Pest and disease detection

Pest and disease detection is a significant IoT application in smart agriculture. Farmers can employ IoT devices such as sensors and cameras to monitor for signs of pest infestations and plant diseases [38]. These sensors can send alerts to farmers when pest activity is detected or when conditions are favorable for disease outbreaks, leading to a proactive approach in minimizing crop damage and eliminating the need for chemical treatments [39]. In addition, prompt pest and disease control allows for quicker responses, leading to improved crop health and yield [40]. IoT can also minimize crop losses through the reduction of extensive pesticide applications, allowing farmers to reduce pesticide costs [41–45].

With a two-tier pest detection architecture created especially for maize fields, a system was developed using Raspberry Pi 2-enabled sensor units with PIR motion sensors, High Definition (HD) cameras, GPS modules, and nighttime LEDs to detect insect activity and collect geotagged data [38]. These devices transmitted media to a master unit hosting a CNN model for pest classification, enabling real-time remote monitoring via 4G routers and Google Cloud.

A deep learning ensemble model improved the accuracy of pest and disease identification across 45 plant conditions by using data augmentation techniques and combining Clustering-based Region-based Convolutional Neural Network (cluster-RCNN) with Improved Network Compression - You Only Look

Once (INC-YOLO) for multi-scale detection [39]. To reduce complexity while maintaining accuracy, ESA-ResNet34—a lightweight CNN with Depthwise Separable Convolutions and Effective Spatial Attention—achieved high accuracy on resource-constrained edge devices [40].

The influence of meteorological factors on insect outbreaks was modelled using ANN, KNN, Random Forest, and MLR techniques to forecast disease spread based on temperature, humidity, and rainfall [41]. Another CNN-based architecture trained on a comprehensive dataset effectively identified plant diseases using preprocessing methods like scaling, normalization, and augmentation [42].

Real-time detection on large farms was enhanced by drone-based image capture integrated with a CNN model trained on a large dataset, enabling high-precision identification under varying conditions [43]. An integrated system combining expert systems, wireless cameras, environmental sensors, and YOLOv3 provided automated alerts and decision support in rice and wheat fields [44]. Finally, a hybrid platform leveraging UAVs and IoT sensors used crop reflectance and environmental data for early stress diagnosis, integrating multi-modal analytics for comprehensive crop health monitoring [45].

2.2.6. Nutrient management

Nutrient management and crop yield optimization have advanced significantly in recent years as a result of the combination of machine learning (ML), artificial intelligence (AI), and agronomic knowledge. To forecast soil nutrient levels, suggest fertilizers, and maximize usage efficiency, researchers are using a variety of models, from deep reinforcement learning to neural networks and ensemble learning.

One innovative method formulated nitrogen management as a deep reinforcement learning problem, outperforming conventional empirical techniques by achieving high maize yields with less fertilizer use by deep Q-networks and soft actor-critic algorithms, marking a shift from static recommendations to dynamic decision-making [46]. Prediction capabilities were further expanded by using a feed-forward neural network trained on soil composition, yield, and climate data to create a supervised learning-based crop and fertilizer recommendation system, achieving 97% accuracy in crop-fertilizer combination prediction [47].

Artificial neural networks and remote sensing were used to estimate soil nutrients without the need for laboratory testing. A mobile application utilized a Multi-Layer Perceptron (MLP) for real-time nutrient prediction, while another model combined Sentinel-2 satellite imagery and weather data with machine

learning algorithms like Random Forests. These models showed high prediction accuracy (Root Mean Square Error thresholds and 93.00% accuracy), enhancing access to precision fertilization, especially in rural areas [48, 49]. The significance of timing and flexibility in fertilizer application was addressed through a recommender system using data from a network of farms. Recursive Feature Elimination (RFE) optimized features, and models such as Random Forest, GBM, and Neural Networks forecasted optimal fertilizer application times with 85.00% accuracy [50].

Visual data was explored for nutrient deficiency detection. Using Convolutional Neural Networks (CNNs) to evaluate leaf photos for nitrogen insufficiency led to a 20.00% reduction in nitrogen use, a 10% increase in yield, and the development of an 80.00%-accurate image-based diagnostic tool [51]. A general-purpose Artificial Neural Network (ANN) trained on soil and climate data reduced fertilizer costs by 18.00% and matched nutrients to specific crops with 88% accuracy, showing economic advantages of AI-based nutrient planning [52]. The power of ensemble deep learning architectures—such as GRU, BiLSTM, and Deep Belief Networks (DBNs)—was shown in soil nutrient and pH level classification, achieving over 92% accuracy and demonstrating the value of deep temporal feature extraction for soil health monitoring [53].

When taken as a whole, these works show a progressive landscape of advancements, ranging from image recognition, mobile computing, satellite data integration, and policy-learning to real-time suggestions. Despite differing methodologies, they collectively aim for effective, data-driven nutrient management in sustainable agriculture.

2.2.7. Greenhouse monitoring

The application of IoT in greenhouse monitoring can improve agricultural efficiency and sustainability [57]. IoT devices are mainly used in greenhouses to maintain optimal environmental conditions such as humidity, light, and temperature [54]. It conserves water, monitors moisture levels, and uses real-time data to schedule irrigation [55]. Farmers can monitor various aspects of greenhouse conditions that affect plant growth and health. These environmental parameters can be calibrated and remotely accessed by farmers to prevent significant crop losses, crop disease, and pest attacks and to optimize energy consumption [60]. Also, plant health and growth in greenhouses can be tracked remotely [59].

Researchers are combining machine learning, computer vision, and real-time sensor data to optimize all facets of controlled-environment agriculture, from

disease detection and yield estimation to crop monitoring and microclimate prediction. The field of smart greenhouse innovation is changing quickly.

One study raised the standard for microclimate control by forecasting temperature, humidity, and carbon dioxide (CO₂) levels in a smart melon greenhouse 30 minutes in advance. They compared several models using real-time sensor data and discovered that Extreme Gradient Boosting (XGBoost) was the most accurate, obtaining R² values above 0.96 for all environmental factors. Their method enables growers to proactively predict and modify growing conditions, which is a fundamental step in precision agriculture [54].

Another study used LSTM-based Recurrent Neural Networks trained on microclimate data from greenhouses in Belgium and the UK to expand predictive analytics to plant growth and yield estimation. Their findings demonstrated that temporal modeling is essential when working with long-term biological responses in plants, with LSTM outperforming other models such as SVR and Random Forests [55].

A UAV system that employs LiDAR and RGB-D imaging was introduced for real-time tomato counting and weight estimation. In just 10.5 seconds, the machine flew over tomato rows with an astonishing 94.4% counting accuracy and 87.5% weight estimation. This represents a significant advancement in crop inventorying and automated harvesting logistics [56].

Plant health and growth monitoring heavily relies on visual sensing. A CNN-based approach to identify leaf diseases achieved over 97% training accuracy and demonstrated particularly high energy efficiency with 44% lower battery usage, tackling a significant issue in IoT-enabled agriculture: power sustainability [57].

Deep learning models such as SSD and YOLOv4 Tiny were developed to identify tomatoes at different ripening stages, even in the presence of occlusions. The YOLOv4 Tiny was notable for its real-time inference speed (5 ms), which is essential for embedded systems and mobile platforms, even if Single Shot Multibox Detector (SSD) MobileNet v2 provided superior accuracy (F1-score: 66.15%) [58].

To detect crop stress levels, researchers creatively classified physiological data such as leaf temperature and photochemical reflectance index (PRI), in combination with microclimate data. Their testing accuracies exceeded 89% through the use of Multilayer Perceptron (MLP) and Gradient Boosting, bringing plant health diagnostics closer to temperature control and precise fertigation [59].

An improved YOLOv5 model addressed the ongoing issue of greenhouse pests, extending monitoring to

pest management. With F1 scores as high as 0.99 and detection precision increased to 96% with ingenious data augmentation (copy-pasting), this kind of automated, fine-grained pest monitoring is essential for lowering crop losses and chemical misuse [60].

From real-time environmental sensing and prediction [54, 55] to plant-level monitoring and response [57, 59], to object-level precision [56, 58, 60], these works collectively demonstrate a symbiotic progression. Every system works toward a common goal: data-driven, autonomous, and sustainable greenhouse agriculture in which artificial intelligence (AI) enhances and supports biological growth processes.

2.2.8. Agricultural drones

Drones equipped with various smart sensors can capture high-resolution images and data on crops and soil conditions. Drones can create detailed 3D images of fields for soil analysis and seed planting planning pattern [67]. IoT-enabled drones can monitor soil moisture level, nutrient content (nitrogen assessment), and weather conditions, and this information can be provided to the farmers [61, 67]. Also, drones can be used to target spraying of pesticides and fertilizers, leading to improved crop health [65]. Therefore, smart agricultural drones provide farmers with aerial surveys of their farms, capturing high-resolution images and data to enhance crop health and quality [68, 69].

Precision agriculture has greatly improved thanks to the combination of artificial intelligence (AI) and unmanned aerial vehicles (UAVs). According to recent studies, UAV-based systems are being used for field management, yield estimation, crop health monitoring, and actionable insights.

A quadcopter drone system with high-resolution photography and an analytical platform based on convolutional neural networks (CNNs) was created for the purpose of assessing crop health in real time [61]. By automating the identification of leaf diseases and facilitating quick, precise data collection, the system significantly outperformed conventional field scouting methods and promoted more adaptable crop management.

In a comparable application, a deep learning-based UAV approach was used for counting coconut palm trees [62]. The researchers' mean average precision increased significantly from 0.65 to 0.88 by using the YOLOv7 object detection model pretrained on the Common Objects in Context (COCO) dataset and supplemented with synthetic training data created by repositioning trees in drone photos. This demonstrates how well synthetic augmentation works to train reliable agricultural models.

A novel unsupervised learning technique was applied to solve weed detection using UAV imagery to detect crop lines and identify interline weeds [63]. With only slight accuracy variations compared to supervised methods (1.5% in spinach fields and 6.0% in bean fields), the system showed promise for scalable weed monitoring.

Pollination performance in oilseed rape fields was evaluated using UAV-based remote sensing [64]. Flower coverage, a stand-in for pollination activity, was measured using high-resolution RGB orthomosaics and K-means clustering. The method's efficacy was validated by a strong negative correlation ($r = -0.92$) with expert judgments.

A deep learning architecture for viticulture used multispectral UAV data to detect vine diseases [65]. Visible and infrared images were aligned using a custom registration method and classified as background, shaded, symptomatic, or healthy using a fully convolutional neural network, achieving accuracy over 92% at the grapevine level.

A CNN-based system was developed to refine satellite-derived NDVI maps using UAV imagery, enhancing crop condition assessments [66]. High-resolution vegetation vigor maps were generated using clustering, improving precision for vineyard management decisions.

A smart crop-monitoring architecture that integrates UAVs, IoT sensors, and machine learning was also developed [67]. Using CNNs and fast recurrent neural networks, the system classified crop abnormalities by preprocessing UAV data and incorporating environmental and historical records to facilitate proactive planning.

When taken as a whole, these studies demonstrate the increasing complexity and variety of UAV-based agricultural solutions. The precision, effectiveness, and sustainability of contemporary farming methods are improved by UAVs combined with AI, which offer scalable, data-driven solutions for anything from pollination monitoring and vegetation indexing to disease identification and yield estimation. Table 2 shows the Internet of Things application in smart agriculture.

3. IoT communication technologies in agriculture

Several communication technologies (CTs) have gained prominence in smart agriculture. These technologies could aid precision farming, monitoring environmental conditions, the dissemination of agricultural information and controlling various aspects of farm operations. Environmental data and other related information in agriculture can be

transmitted with high precision. CTs support various agriculture activity including crop management, livestock monitoring and supply chain management. The key components of CTs include internet, mobile applications, IoT devices, and wireless communication networks. The most widely used communication technologies in agriculture are as follows:

3.1. Cellular networks (2G, 3G, 4G, 5G)

Cellular networks (CNs) are widely used for IoT applications in agriculture due to their broad coverage and ability to transmit data over a long distance [70, 71]. For instance, farmers can use 4G or 5G network to connect remote sensors that monitor soil moisture and weather conditions. The collected data can be sent to a central server for analysis, allowing farmers to schedule irrigation and manage crops.

3.2. Low power wide area networks (LPWAN)

LPWAN technologies such as LoRaWAN and NB-IoT, are designed for low-power long-range communication, making them suitable for large area agricultural applications [16, 72]. Soil moisture equipped with LoRaWAN can transmit data over several kilometers, enabling farmers to monitor soil conditions across vast fields without the need for frequent battery replacement.

3.3. Wi-Fi

Wi-Fi commonly referred to as wireless fidelity is used in greenhouse and farms where stable internet connection is available. It allows for high-speed data transfer between IoT devices and local servers. Typically, in a greenhouse, Wi-Fi-connected environmental sensors can monitor temperature, humidity, and light levels, sending real-time data to a central system that adjust conditions automatically to optimize plant growth.

3.4. Bluetooth and ZigBee

Bluetooth and ZigBee are short-range communication technologies for connecting devices within a localized areas such as a farm or green house. For instance, Bluetooth-enabled livestock trackers can monitor the health and location of animals, transmitting data to a nearby smartphone or tablet for easy access by farmers [73, 74].

3.5. Satellite communication

Satellite communication provides a viable solution for data transmission in remote agricultural areas

Table 2. IoT applications in smart agriculture.

Application area	Technology description	Crop/Animal species
Smart irrigation system	optimizes water use by utilizing automated irrigation controllers and soil moisture sensors.	Cotton, vegetables, gardens
Livestock monitoring	Wearable sensors (tags, collars) monitor the location, activity, and health of animals.	Cattle, pigs, poultry birds
Crop health monitoring	Drones and satellites are examples of remote sensing systems that evaluate crop health and identify stress early.	Cereals, legumes, nuts, spices
Climate and weather monitoring	Data on temperature, humidity, precipitation, and wind are gathered by on-field weather stations.	Tropical crops (e.g. sugarcane), temperate crops (e.g. wheat, Oats and gram), crops affected by climate change (i.e. soy and wheat)
Pest and disease detection	AI systems and sensor-based traps are used to find and identify crop pests or diseases.	Vegetables, cotton
Nutrient management	Fertilization is guided by nutrient levels measured by soil sensors and portable analyzers.	Vegetables, fruit crops, field crops, groundnuts
Greenhouse monitoring	Temperature and illumination are automatically controlled by embedded environmental sensors.	Fruits, vegetables, herbs, flowers
Agricultural Drones	Unmanned aerial vehicles (UAVs) are utilized for field imaging, seeding, and spraying.	Grains, cereals, vegetables fruits

with limited internet connectivity [75]. Farmers can use satellite-based IoT system to monitor crop health and soil conditions in remote fields and receive data that can help farmer to manage resources effectively.

4. The impact of IoT on the agricultural industry

Countries striving for sustainability and green agriculture have begun to focus on innovative technology such as Artificial Intelligence (AI), Machine Learning, big data, and deep learning. IoT provides agriculture with plethora innovation prospects that enhance productivity, resource efficiency, monitoring, and management of crops and livestock. IoT technology contributes to agricultural sustainability by enabling better management of natural resources. This is particularly important as the global population continues to grow and food demand increases. So, adopting IoT in agriculture assists in maintaining soil health and reducing climate impact on farm practices, and improving food security. also, the integration of IoT has significant impact on productivity and sustainability [76]. With real-time data analytics, farmers can make informed decisions that can lead to higher yields. For instance, monitoring crop health through connected devices aids pest control, nutrient management and prevent crop losses. Furthermore, the use of IoT technologies can significantly reduce water and electricity waste, labor cost and also increase income for farmers. Automation of routine tasks via connected devices allows farmers to focus on strategic activities, leading to secure modernized agricultural sector.

5. Emerging technologies advancement in IoT for agriculture

Emerging Technologies is ushering in a new era of agriculture. Emerging technologies such as agribots, nanotechnology, and wearable sensors are paving the way for new agriculture solutions such as autonomous agribots, agricultural materials, and self-driving tractors. The following are emerging technologies for agriculture sustainable future

5.1. Agricultural robots (Agribots)

With the increasing demand for labor and shortage of workers in agriculture, Agribots are gaining traction [77]. Agribots (autonomous robots) can gather real-time data on soil conditions, crop health, and environmental factors. The integration of IoT and agribots can help to automate various farming operations such as planting, harvesting, and monitoring crops. Also, agribots can autonomously navigate fields, apply fertilizers, and harvest crops based on real-time data [78]. The synergy between IoT and Agribots is paving the way for a new area in agriculture.

A flexible robotic system for precision farming applications that combines unmanned ground vehicles (UGVs) with unmanned aerial vehicles (UAVs) was introduced in 2016. The system developed algorithms for multispectral perception and combined ground-based and aerial devices to monitor nitrogen nutrition status, crop density, and weed pressure. Agricultural-specific mapping and navigation systems were put into place, proving the system's efficacy in selective spraying and collaborative mapping without the need for human involvement [77].

An autonomous robot for accurate and economical tomato harvesting was created in 2024. To identify and gauge the maturity of tomato trusses and fruits, a multi-task YOLOv5 model was employed. Seven semantic key points on the pedicel were predicted by a deep learning algorithm to help with path planning and reduce touch during harvesting. In commercial greenhouse settings, an average harvest time of 32.46 seconds per tomato was attained, resulting in an 86.67% harvest success rate [78].

A modular, reconfigurable robot platform was created in 2024 to assist with a variety of agricultural activities and enhance the transfer of knowledge from research to practical applications. Five configurations for various agricultural purposes were displayed, demonstrating the robot's adaptability and versatility in a variety of actual agricultural situations [79].

A method was developed to enable robots to move between crop rows beneath the canopy by fusing model predictive control with monocular RGB vision perception. The CropFollow system outperformed a LiDAR-based system, which averaged 286 meters per intervention, with an average of 485 meters [80].

A multipurpose electric field management robot capable of performing duties like weeding, pesticide spraying, and crop data collection was created in 2024. The robot features an integrated navigation system that uses RTK-GNSS, LiDAR, and cameras, as well as four steering modes: Ackermann, four-wheel, crab, and zero-radius. The crab steering mode achieved a maximum tracking error of 43.35 mm and an average lateral error of 20.75 mm in field tests, indicating outstanding trajectory tracking accuracy [81].

A technique for automatic weed scouting without prior species information was created, employing clustering algorithms to distinguish between distinct plant species and deep convolutional neural networks to discover low-dimensional attributes for plant representation. The method successfully separated cotton plants from grasses in field data gathered by the AgBotII robot, indicating the possibility of unsupervised weed scouting [82].

Using IoT technologies, an autonomous robot was developed to continuously monitor plant conditions. Equipped with integrated sensors and a line-following navigation system, the robot captures plant images, which are then transmitted via IoT to a monitoring mobile application. The system enhanced decision-making in crop management by enabling real-time plant condition monitoring [83].

5.2. Advanced drones (ADs)

Advanced Drones are becoming an integral part of smart farming [79]. AD is currently being used for

various farming activities including crop monitoring, soil analysis and precision spraying of fertilizers and pesticides [24, 80]. This technology combines IoT devices, sensors and advanced algorithms to monitor and detect various environmental data for predictive analysis and crops assessments. For a detailed review of the related work on the use of drones in smart farming, please refer to [Section 2.2.8](#).

5.3. Machine learning (ML) and Artificial Intelligence (AI)

ML and AI are increasingly popular in agriculture for data analysis [84–92]. One key motivation for this is the use of AI and ML algorithms in enhancing data analysis capabilities. These predictive techniques can allow farmers to predict crop yields, detect disease early and optimize planting and harvesting schedules. The synergistic combination of these technologies with IoT can improve productivity and farm sustainability.

Recent advancements in machine learning (ML) and deep learning (DL) have significantly impacted crop yield prediction, offering more accurate, efficient, and scalable solutions for agricultural forecasting. A range of studies has employed diverse methodologies to enhance yield prediction models, incorporating various data sources, including weather patterns, soil quality, and satellite imagery, to create predictive frameworks suited to different regions and crops.

One prominent example is the development of a hybrid machine learning model for forecasting agricultural yields in India. By combining the best-performing algorithms, such as Decision Tree (DT), XGBoost, and Random Forest (RF), the model achieved an impressive 98.60% accuracy. This 'Crop Yield Predictor' tool offers an accessible solution for real-world applications, providing farmers with a practical tool for predicting crop yields based on historical data and machine learning techniques [84].

In a similar vein, a study focused on forecasting maize and Irish potato yields using environmental data such as rainfall and temperature. The Random Forest (RF) model outperformed others, achieving R^2 scores of 0.875 and 0.817 for Irish potatoes and maize, respectively. This highlights the importance of environmental factors in crop yield prediction, emphasizing the power of RF in handling real-world agricultural data [85].

Furthermore, a system was created to assess soil fertility, which is crucial for optimizing crop production. By applying classifiers like K-Nearest Neighbors (KNN), Naive Bayes (NB), and Decision Trees (DT) to soil data collected from Gunupur, India, the system

effectively classified soil fertility, aiding agricultural planning and enhancing soil management strategies for farmers [86].

A more region-specific study used ML and DL techniques to predict crop yields in Rajasthan, India. Several models, including Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM), were tested on datasets for five different crops. The Random Forest model achieved the best performance with an R^2 score of 0.963, underscoring its suitability for accurate yield prediction in Indian agricultural settings [87].

Another compelling study analyzed 28,242 global crop samples, comparing multiple ML algorithms, including RF, Extra Trees (ET), and Artificial Neural Networks (ANN). The ET model outperformed the others with an R^2 of 0.9873, demonstrating its high accuracy and efficiency in global crop yield prediction. This broad-scale analysis indicates the potential of ML in improving agricultural forecasting at a global level [88].

Further advancement in crop yield prediction integrated Internet of Things (IoT) data with machine learning algorithms. The Crop Yield Prediction Algorithm (CYPA) utilizes real-time climatic data gathered via IoT sensors to forecast yields, highlighting the significance of IoT in providing real-time, localized, and highly accurate agricultural predictions [89].

A more holistic approach was taken by integrating machine learning models with real-time satellite and sensor data. The system analyzes soil, crop identification, and irrigation needs, offering farmers actionable insights for resource optimization. This integrated system demonstrates how combining multiple data sources can contribute to more sustainable and efficient farming practices [90].

Moreover, a study focused on crop selection and yield prediction using machine learning techniques, with Random Forest regression achieving an impressive R^2 score of 0.96. This work also highlighted the potential of Naïve Bayes classifiers in accurately predicting crop types, achieving a remarkable 99.39% accuracy in crop prediction, which is a valuable tool for farmers in selecting the most suitable crops based on environmental conditions [91].

Lastly, a study exploring the effectiveness of Support Vector Regression (SVR) alongside dimensionality reduction techniques like Principal Component Analysis (PCA) for predicting crop yield demonstrated high accuracy (97%) in forecasting agricultural yield [92].

Collectively, these studies illustrate the transformative potential of machine learning and deep learning in precision agriculture. From improving soil management to optimizing irrigation and enhancing

yield forecasts, these technologies are poised to play a pivotal role in shaping the future of sustainable agriculture.

5.4. Remote control of agricultural machinery

Remote control technologies (RCTs) of agricultural machinery is a new direction in IoT applications for agriculture. The IoT and RCT rely on intelligent sensors to improve farm operations, efficiency, and safety of farm machinery [93, 95]. The synergy of this technology with IoT enable farmers to remotely control their machinery using smartphones, or tablets. It also facilitates predictive maintenance of agricultural machinery in real-time [97].

The landscape of agriculture is rapidly evolving with the integration of cutting-edge technologies aimed at improving precision, efficiency, and accessibility. One of the most exciting advancements in this field is the development of autonomous and remote-controlled systems designed to assist farmers, regardless of their experience level.

For instance, a remote tractor operating system designed for novice users was introduced in 2023. This system, utilizing a gamepad-like interface, simplifies the control of tractors in challenging environments where autonomous driving may not be feasible. Field trials demonstrated their success, with operators able to navigate and till fields with remarkable precision, aligning implements within just 0.5 meters of their intended targets [93].

Further enhancing the capabilities of agricultural machinery, an IoT-based control platform for unmanned farms was developed, enabling the remote operation of multiple agricultural machines. This platform dramatically reduces labor needs and boosts operational efficiency by allowing precise coordination between machines. With high synchronization and impressive mapping accuracy, errors were kept under 3 cm, making it highly effective for large-scale farming [94].

On a more immersive front, a teleoperation system that integrates virtual reality (VR) with UAV-based digital mapping for precision agriculture was introduced. This system outperforms traditional video-based remote operations, offering operators complete situational awareness and improved control accuracy. By utilizing advanced Structure from Motion algorithms and a closed-loop VR control system, it enables operators to engage with their equipment as if they were physically present in the field, providing an intuitive and effective means of managing agricultural tasks [95].

Precision in navigation and control is crucial in the realm of autonomous farming, especially when

dealing with unpredictable terrains. A real-time receding horizon estimation and control (RHEC) system for tracked field robots was developed to ensure accurate navigation, even in challenging soils. This system achieved a mean tracking error of just 4.23 cm and computation times under 1 ms, proving its reliability for tasks such as planting and harvesting [96].

In another significant development, an autonomous tractor control system was created using RTK-GPS for ultra-precise path tracking. This system was tested on a Tianjin TieNiu crawler tractor and showed minimal linear route tracking errors, with maximum deviations of 4.09 cm, ensuring the tractor's precise autonomous navigation [97].

Not all autonomous systems in agriculture rely on GPS. A vision-based navigation system for agricultural robots, capable of operating in the absence of GPS, was introduced. Deployed on the BonnBot-I platform, this system uses onboard cameras to track crop rows, with an average accuracy of 3.82 cm across a variety of field conditions, making it adaptable to different farming environments [98].

The integration of AI into autonomous systems has led to breakthroughs in real-time crop management. An autonomous agricultural robot was developed to incorporate a convolutional neural network (CNN) for real-time weed detection. The robot was able to identify and classify weeds with high accuracy, showcasing the role of AI in reducing herbicide use and promoting sustainable farming [99].

These advancements, from intuitive remote tractor systems to AI-driven weed detection robots demonstrate how emerging technologies are transforming agriculture. By integrating IoT, AI, and autonomous systems, farmers can perform tasks with greater precision, efficiency, and sustainability, ultimately paving the way for a new era in agricultural productivity.

5.5. Autonomous tractors

Autonomous tractors, often known as self-driving cars, are transforming the face of agricultural technology. These tractors use modern technologies such as sensors, cameras, and artificial intelligence to navigate and make decisions while driving autonomously, hence eliminating the need for human participation. The concept of self-driving tractors has been around for decades, but recent advancements in technology have made it fruition. One of the main benefits of self-driving tractors is their ability to increase operational efficiency. With autonomous tractors, the risk of human error is significantly reduced, as the tractor is equipped with sensors that can detect and respond to potential hazards faster than a human driver. This

technology has the potential to optimize resource use, such as water and fertilizers. Moreover, autonomous tractors have the potential to reduce greenhouse gas emissions due to the ability to operate in hybrid modes as electric or hybrid. However, there are still challenges to overcome, such as regulatory and ethical concerns, before we see widespread adoption of autonomous tractors. Nonetheless, the future of agriculture looks promising with the advancement of this technology.

The development of autonomous tractor-trailer systems has benefited significantly from advances in nonlinear model predictive control (NMPC). A decentralized tube-based NMPC framework was introduced to enhance robustness against disturbances and ensure coordinated behaviour in tractor-trailer dynamics [100]. In a related work, centralized NMPC was applied with an online learning mechanism, improving real-time control efficiency and adaptability in unstructured field environments [101].

Handling parameter uncertainty and external disturbances remains a key challenge in trajectory tracking. A recent study introduced a robust control framework capable of mitigating such uncertainties while maintaining path fidelity, even under adverse field conditions [102]. Complementing this, nonlinear guidance laws have been successfully used to simplify path-following control for autonomous tractors, demonstrating effective course adherence on complex trajectories [103].

Basic path-following systems have also evolved, with Global Positioning System (GPS) and Real-Time Kinematic (RTK) technologies enabling highly accurate driverless tractor control systems with average errors in the centimeter range [104]. Expanding beyond classical control methods, type-2 fuzzy logic controllers have shown promise in managing uncertainties and nonlinearities typical of off-road agricultural environments [105].

Robust planning and control approaches are further reinforced through formal modelling of uncertainty sources in autonomous tractor-trailer systems, highlighting the need for adaptive algorithms capable of adjusting to varying terrain and task complexity [106]. Supporting these efforts, recent work on all-terrain autonomous robots has demonstrated the viability of navigation algorithms tailored for agricultural settings, particularly where obstacle avoidance and terrain irregularities are prominent [107].

5.6. Nanotechnology and IoT integration

Nanotechnology is a novel areas that use materials at nanoscale to create agricultural products with unique properties and traits [108]. Nanomaterials

are being developed to facilitate early detection of pathogens in crops and produce crops with enhanced traits that can adapt to climate change and resist pest and disease. Also, nano pesticides and nano fertilizers are new areas of application of nanotechnology in agriculture. Nanotechnology can be used to improve soil quality and materials such as nano zeolites and hydrogen can enhance soil structure, water retention and nutrient availability [110].

The convergence of nanotechnology and the Internet of Things (IoT) is revolutionizing modern agriculture, offering farmers the tools to make real-time, data-driven decisions that enhance productivity, efficiency, and sustainability. This smart integration enables precise monitoring of crop health, soil conditions, and environmental factors—ushering in a new era of precision agriculture.

Zhang and Liu [108] pioneered an IoT-based agricultural monitoring system using nano-enhanced sensors such as SHT-11 for humidity, BH1750 for light, and MS-10 for soil moisture. The system leveraged the ZigBee protocol for efficient wireless communication, proving effective in real-time field tests for crop condition optimization.

Nanotechnology also plays a central role in targeted crop and soil diagnostics. Samreen et al. [110] highlighted how nano sensors enable the detection of nutrient levels, moisture content, and early pest infestations. These miniaturized devices operate with high sensitivity and specificity, allowing for micro-level interventions that reduce resource waste and environmental harm.

Dinesh et al. [109] presented a broader perspective by integrating nano-biosensors with satellite-based agricultural systems, forming a cyber-physical framework for real-time soil fertility analysis, crop health assessment, and input management. This allowed for precise spatial decisions that minimize over-application of fertilizers and pesticides while maximizing yield.

Anuja et al. [111] emphasized the importance of nano-sensors in decision-based farming, where inputs are applied based on data from real-time environmental tracking. Their work detailed the use of nanoscale biosensors combined with satellite imaging to guide pesticide and fertilizer delivery, improving both yield and environmental safety.

Moreover, recent trends in agricultural robotics and automation are also beginning to incorporate nano-enhanced IoT systems. These systems, equipped with nano-sensors, can autonomously navigate fields, identify plant stressors, and deliver remedies with surgical accuracy. This not only reduces human labor but also enhances farm-level autonomy and scalability.

Beyond direct sensing, researchers are exploring how nanomaterials—such as carbon nanotubes, silver nanoparticles, and quantum dots—can be integrated with IoT devices to improve sensor durability, biocompatibility, and response time [112]. These materials increase the reliability of long-term agricultural monitoring systems, particularly in harsh field environments.

In summary, the integration of nanotechnology into IoT-based agriculture systems supports a paradigm shift toward precision, sustainability, and automation. These innovations empower farmers with actionable insights, reduce dependency on harmful chemicals, and ensure that inputs are applied only when and where needed—paving the way for climate-smart, resource-efficient farming.

5.7 Wearable sensors in agriculture

The demand for wearable sensors is increasing in precision agriculture. One key reason for its high demand is due to non-invasive technique employed in its operation. These sensors are currently used in crops and animals to collect real-time data for optimal growth of livestock and crops. In disease detection, it is mainly used to identify biochemical signals associated with plant animal diseases. The synergetic combination of wearable sensors and IoT can improve efficiency, resource conservation, crop management and disease detection.

An IoT-enabled smart neck-collar combining temperature, pulse-rate, and 3-axis motion sensors was developed to monitor the health of dairy cows. Random-Forest models flagged early health anomalies in 150 dairy cows with 92% accuracy, enabling prompt treatment and reducing veterinary costs [113].

A chip-scale colorimetric nano-biosensor was fabricated to quantify soil nitrate- and phosphate-nitrogen in less than two minutes in the field. On 18 Indian farms, the tool achieved $R^2 = 0.89$ compared to laboratory results and reduced fertilizer use by 25% [114].

PlantRing, a silk-based stretchable strain sensor, was introduced to track organ-circumference dynamics in tomatoes. A wireless mesh of 300 rings was used to automate irrigation decisions, reducing greenhouse water use by 20% [115].

Hyperspectral imagers mounted on drones detected wheat stem-rust seven days before visual symptoms appeared. The Support Vector Machine – Random Forest (SVM-RF) pipeline discriminated healthy, mild, and severe infections with 85% overall accuracy, safeguarding yield potential [116].

Cattle behavior recognition from accelerometer data was achieved by leveraging in-situ cross-device model learning, improving real-time recognition accuracy in monitoring animal activities and welfare [117].

A leaf-mounted capacitance sensor was developed to continuously monitor foliar transpiration and solar irradiance as indicators of plant water status. Continuous data correlated with stem-water potential, enabling fine-grained drip-irrigation scheduling [118].

5.8. Renewable energy and IoT integration in agriculture

Unreliable grid energy system has long been identified as main challenge of agriculture, especially in remotes areas [119]. The integration of Internet of Things and renewable energy sources like wind, Solar, Solar thermal and battery storage system such as fuel cell and hydrogen can compensate for grid power unreliability and provide remote access of energy to farm operations. Also, the renewable energy can power vital farm equipment and ensure that these systems remain operational even in off-grid locations.

In the pursuit of sustainable agriculture, researchers are harnessing the power of IoT and renewable energy to revolutionize farming practices across diverse regions. A low-cost, open-source smart farming solution was designed to support small to medium farms in arid and sub-Saharan regions. The system uses Arduino-based sensors to monitor key parameters like soil moisture, temperature, humidity, and water level, while smart relays automate irrigation and lighting. It is powered entirely by solar energy and managed by a Raspberry Pi running Node-RED, with fuzzy logic enabling intelligent irrigation decisions and Message Queuing Telemetry Transport (MQTT) handling remote monitoring. Field trials demonstrated impressive results: water usage was reduced by 71.8%, and soil moisture was consistently maintained between 57%–65%, indicating both efficiency and environmental sustainability [119].

A comprehensive smart agriculture framework integrating solar panels, Battery Energy Storage Systems (BESS), IoT, and precision robotics has also been introduced. An Espressif Systems 32-bit (ESP32) microcontroller collects and manages real-time energy and environmental data, feeding it into the Blynk IoT platform for seamless visualization and control. A Bluetooth-enabled robot applies chemicals accurately based on sensor input, enhancing precision in farm management. The system not only improved crop health and irrigation efficiency but also achieved a 27% reduction in CO₂ emissions and lowered the

Levelized Cost of Energy from \$0.300 to \$0.170 per kWh—a significant economic and environmental gain [120].

A smart agriculture framework designed for regions like Bangladesh aimed to improve farming through real-time monitoring and decision-making. The system includes soil moisture, salinity (via BJT BC548), water level, humidity, and temperature sensors, with Arduino Nano boards processing the data. Data is sent via ESP8266 Wi-Fi modules to the cloud, where farmers can access it through a smartphone app. Powered by solar panels, the system runs independently of external power sources, enabling timely, informed decision-making [121].

An IoT-enabled environmental control system powered by solar energy was developed for Indian oyster mushroom cultivation. It features sensors for temperature, humidity, and light, along with actuators, Raspberry Pi 4 microcontrollers, and adaptive control algorithms for maintaining optimal conditions. The system also integrates battery storage for uninterrupted power. Compared to traditional techniques, it significantly reduced energy usage and carbon emissions, proving effective for sustainable, controlled-environment farming [122].

A smart agriculture monitoring system was created using IoT sensors and renewable energy to automate environmental monitoring and irrigation. Soil moisture, humidity, and temperature sensors are interfaced with an ESP32 microcontroller, which processes and transmits data to a cloud platform via Wi-Fi. Farmers monitor and control the system remotely using a web or mobile app. Powered by solar panels, the system ensures energy efficiency and reduced operational costs while maintaining a reliable power supply [123].

5.9. IoT application in crop storages

Nkanaunena and Chatola introduced a real-time crop storage monitoring solution powered by IoT sensors that continuously track critical environmental parameters—gas levels, humidity, and temperature—within storage facilities. When conditions drift from the optimal range, the system instantly sends alerts, enabling swift corrective actions. This not only helps prevent spoilage but also substantially reduces post-harvest losses by allowing early intervention [124].

To further address the challenges of safe grain storage, Sivathanu et al. designed an intelligent silo monitoring system. It uses sensors to detect CO₂ accumulation, humidity, and temperature, and employs Google Apps Script to analyze and visualize this data. The system includes an emergency protocol capable of releasing toxic gases, when necessary, thus

preventing dangerous build-ups and enhancing both grain preservation and operator safety [125].

Pushing the boundaries of environmental surveillance, Lydia et al. implemented a sophisticated sensor network across storage warehouses to monitor grain level, temperature, humidity, vibration, carbon monoxide, motion, and smoke. The system utilizes PIC microcontrollers to collect data and GSM modules to upload it to the cloud. Real-time alerts are issued through SMS and mobile apps, enabling rapid response to risks such as fire, pests, or environmental imbalances—effectively lowering spoilage rates and improving overall warehouse safety [126].

Meanwhile, Viviane et al. developed an IoT-based system tailored for both crop drying and storage. By measuring parameters like temperature, humidity, and moisture content, the system ensures optimal drying and storage through automated control of ventilation and heating systems. Data is processed in real-time via a cloud platform, while remote monitoring and real-time alerts enable immediate interventions. This continuous monitoring minimizes mold growth and pest infestation, preserving crop quality and extending shelf life [127].

Focusing specifically on rice grains, Zari et al. deployed IoT sensors in paddy storage units to monitor temperature, humidity, and moisture levels. The data is transmitted to a centralized cloud platform that analyzes it in real-time. Automated adjustments to ventilation and environmental settings help maintain optimal conditions, reducing spoilage and preserving grain quality during storage [128].

Lastly, Doltade et al. presented a comprehensive IoT-based monitoring and control system aimed at enhancing grain storage efficiency and safety. Utilizing a suite of sensors—DHT11 for temperature and humidity, MQ2 and MQ135 for gas detection, and PIR sensors for security—the system is anchored on a NodeMCU ESP8266 microcontroller. Data is relayed to the ThingSpeak cloud for visualization, while the Blynk app provides remote access and alerts. When parameters exceed safe thresholds, the system triggers buzzers, fans, or relays to restore balance. This real-time, automated intervention significantly curbs spoilage risks and enhances overall grain storage management [129].

6. Case studies

The growing demand for sustainable agricultural systems has expanded the application of the Internet of Things (IoT) across various sectors of agriculture worldwide. Numerous real-world examples demonstrate the successful integration of IoT technologies,

which are revolutionizing modern farming practices by enhancing productivity, sustainability, and decision-making processes.

In countries like Israel, which is renowned for its agricultural innovations, farms utilize soil moisture sensors to obtain real-time data on water requirements. These systems help optimize irrigation schedules, reduce water waste, and improve crop health. Similarly, India is leveraging IoT through startups such as AgroStar, which provides farmers with soil sensors that measure nutrient levels and moisture content. This data is transmitted to a mobile app, enabling informed decisions on fertilization and irrigation, thus improving yields while minimizing input costs. In Sub-Saharan Africa, IoT-based irrigation systems for smallholder farmers are being used to automate watering based on soil conditions, resulting in efficient resource use and higher productivity.

IoT applications have also gained significant traction in livestock monitoring. In the United States, companies like Allflex have developed wearable sensors for cattle that monitor health indicators, movement, and behaviour. These devices enable early illness detection and efficient herd management [130]. Australia is actively testing and deploying similar wearable technologies that track cattle activity and detect lameness or other health issues [64]. In Kenya, GPS tracking collars are used for pastoral herds to optimize grazing patterns and reduce livestock loss [97]. Zimbabwe's start-up, Hurukuro, is deploying livestock tracking systems and agricultural drones across the farming value chain, supporting logistics and animal monitoring [134].

IoT-enabled pest and crop health management systems are another major application. Brazil, for instance, uses drones and satellite imagery to monitor crop conditions across expansive soybean and coffee plantations [100]. Additionally, Brazil has implemented sensor-based pest detection systems that can trigger targeted responses such as releasing beneficial insects or localized pesticide application, reducing environmental impact and promoting sustainability [110]. In Argentina, predictive analytics using AI and machine learning models help anticipate pest and disease outbreaks in corn and soybean fields, allowing for timely interventions.

Post-harvest management and supply chain optimization are also benefiting from IoT adoption. China has installed sensors in storage facilities to monitor temperature, humidity, and spoilage in fruits and vegetables, thereby minimizing losses [129]. Spain is currently utilizing RFID tags to monitor produce shipments, ensuring food safety and traceability throughout the supply chain. In Rwanda, sensors are being integrated into food storage systems to help

maintain optimal conditions [133]. The United States is exploring advanced solutions such as blockchain platforms to provide end-to-end visibility in the beef supply chain, enhancing traceability and consumer trust [133].

Precision agriculture driven by data analytics is another emerging trend. In the Netherlands, greenhouse automation is facilitated by intelligent sensors like Priva, which regulate temperature and humidity autonomously to maintain ideal growing conditions [131]. Japan uses AI and predictive models to forecast crop yields and optimize planting and harvesting schedules, especially for staple crops such as rice [92]. Similarly, European nations such as Germany and the Netherlands have adopted the EU's IoF2020 Directive to encourage IoT use in agriculture, improving efficiency and sustainability across the sector [132].

Further advancing digital agriculture, the AGrIDI project spans several West African countries and promotes the adoption of innovative digital technologies, including IoT, to enhance food security and agricultural productivity [135]. Across Europe, various pilot initiatives are being developed to apply IoT for real-time soil monitoring, climate data collection, and crop condition analysis, enabling farmers to make timely and precise agricultural decisions.

7. Challenges of internet in agricultural systems

The integration of the Internet of Things (IoT) in agricultural systems offers several benefits including improved efficiency, crop storage and management, and sustainability. However, it also presents significant challenges such as:

7.1. Security concern

The integration of IoT in agriculture raises significant security issues, including the risk of hacking and data theft. As farms become more connected, they become more vulnerable to cyberattacks, which can compromise sensitive data and disrupt farm operations. Also, there is a risk that collected data could be misused by the third parties, leading to potential violations of personal privacy.

7.2. Cybersecurity concern

With the numerous devices connected to the network, the potential entry point for cyber attacks increase significantly, hackers can exploit vulnerabilities in IoT devices to gain unauthorized access to

sensitive information or disrupt transportation services. Robust cybersecurity measures are essential to protect against these threats.

7.3. Complexity of integration and interoperability

Integrating IoT technologies with existing transportation systems can be complex and resource intensive. For instance, integrating IoT technology with the existing agriculture system pose a great challenge in terms of technicality. Intensive absence of universally accepted communication protocols, diverse data formats and technologies, network complexity, interconnection issue and scalability are major challenges of IoT in agriculture. In addition, integrating smart sensors with farm machinery raises issues on compatibility and connectivity. Counting crop sensor data with environmental data on a computing platform creates data sharing and system integration problems since the data formats and technologies differs, and there is no common technique for data fusion [113]. Interoperability may be difficult to achieve since various technologies differ in terms of data formats and communication protocols. Also, disparity in software, Apps functionalities and hardware capabilities can limit the effectiveness of mobile applications across different platform.

7.4. High implementation costs

High investment cost and system complexity are another crucial barrier in deploying IoT technologies in agriculture. Smart agricultural systems necessitate substantial investments in hardware, software, and infrastructure. This can be particularly challenging to adoption for smaller farm holders with limited budgets, since many existing agricultural systems may require huge cost to accommodate significant upgrades of IoT systems. Furthermore, implementation, maintenance and upgrade of IoT technologies in agricultural systems are complex, and require advanced analytics capabilities and infrastructure in data management, Artificial Intelligence, and IoT technology.

7.5. Lack of awareness and information

Awareness and information are one of the major barriers of adopting IoT in agriculture. Farmers need to be aware of connectivity issues, data management complexities, and the need for secure systems to protect sensitive information. Farmers can be well-informed on the state-of art in IoT through public enlightenment, education, training programs and collaboration with technology provides.

7.6. Connectivity issues

Inconsistent connectivity is one of the main challenges that the reliability of IoT devices in agriculture. IoT system rely heavily on reliable connectivity to function effectively. Any distortion in network signals or network breakdown can lead to significant issues such as gap in data collection and transmission, traffic congestion, and delay response.

8. Discussion of the survey

Precision, efficiency, and sustainability have all increased significantly because of the application of Internet of Things (IoT) technology in agriculture. Some patterns and trends show up in the case studies and application areas that have been analysed. For example, among the most developed and extensively used applications are intelligent irrigation systems and livestock monitoring technologies, which are motivated by observable cost reductions and increases in output. However, because of high expenses, a lack of digital literacy, and poor infrastructure, adoption is still restricted in many low-income and smallholder agricultural areas.

The capacity of IoT applications to produce real-time, detailed data that enhances decision-making is one of its main advantages. A scalable solution to some of agriculture's most urgent problems, such as climatic variability, pest outbreaks, and wasteful input utilization, is provided by technologies like drones, smart sensors, and machine learning models. The survey shows that, despite these benefits, development and implementation vary by location and farming scale.

Numerous difficulties still exist, such as:

- Problems with data standardization and interoperability make it challenging to integrate across platforms and devices.
- Issues with data security and privacy, especially with cloud-based solutions.
- Real-time data transmission is hampered in remote rural locations by energy and connectivity constraints
- High upfront costs and a dearth of alternatives specifically designed for smallholder farms.

Furthermore, many developing regions are still only building basic sensor networks, while developed nations are experimenting with AI, blockchain, and predictive analytics. This draws attention to a digital divide that requires localized technology development, capacity training, and policy support.

Research-wise, there aren't enough long-term performance assessments of these systems available

right now, particularly in settings with limited resources. Furthermore, interdisciplinary cooperation is required to match technical advancements with the ecological and socioeconomic realities of various farming systems.

9. Future directions

The future of IoT in agriculture poises significant transformation, driven by advancement in technology and increasing demand for efficiency and food security. However, some areas in smart agriculture that require additional future directions are as follows:

- Security and privacy are crucial and serious issues in agriculture industry. Cyber-attack in agriculture infrastructure can be costly and fatal to national security, public safety and economy. Future research should focus on developing advanced encryption and anonymization techniques. Also, research into adaptive cyber security measures that can respond to evolving threats can be exploited for maintaining the integrity of IoT systems.
- Exploring innovative funding models and cost-sharing mechanisms can facilitate the adoption of IoT technologies, particularly in resource-constrained environments.
- Promoting industry-wide standards for IoT devices can enhance interoperability and allow seamless integration across different platforms and technologies.
- Implementing strict data governance policies can help protect user privacy. This includes clear data usage policies, user consent mechanisms, and regular audits of data handling services.
- The use of blockchain technology can be adopted to improve security, efficiency and data management across various transportation networks. The synergetic integration of blockchain technology with IoT and AI can lead to smarter, reliable, and sustainable transport systems that can adapt to changing environmental conditions and user needs.
- Green agriculture system can be a policy imperative for many developing countries, especially in Africa, to reduce food scarcity and improve the productivity and food security of agriculture aspect such crop management, livestock monitoring and smart farming. This is in line with the United Nations Sustainable Development Goal (UNSDG 1, 2,2,11, 15) on safe, affordable, accessible, and sustainable transport systems for all by 2030. Sustainable transport systems are vital for combating climate change and improving air quality in cities.

10. Conclusion

The adoption of IoT in agriculture signifies a revolutionary change toward data-driven, efficient, and sustainable farming methods. The broad role of IoT in tackling the intricate problems facing the agriculture industry, like irrigation, livestock monitoring, resource inefficiency, food insecurity, and crop health monitoring, has been examined in this paper. IoT makes it possible to precisely and automatically control agricultural processes using smart sensors, cutting-edge communication technologies, and real-time monitoring systems. This leads to enhanced resource management, decreased waste, and increased output.

Additionally, predictive decision-making, crop and livestock management, and operational efficiency are improved by the convergence of IoT with cutting-edge technologies including artificial intelligence, machine learning, big data analytics, cloud computing, and nanotechnology. From greenhouses to far fields, communication technologies like cellular networks, satellites, and LPWAN guarantee reliable data transfer in a variety of agricultural environments.

The analysis also highlights how sensor technology is developing and how embedded systems hold promise for upgrading agricultural processes. The ongoing development and uptake of IoT and related technologies is crucial for accomplishing sustainable development goals, guaranteeing food security, and fostering economic resilience as agriculture faces increasing demands because of population expansion and climate change.

In conclusion, IoT-enabled agriculture is essential for the future and not just a fad. To fully exploit the potential of these technologies and to make smart farming scalable and accessible across economies and regions, more research, funding, and governmental support will be needed.

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References

1. R. Abbasi, P. Martinez, and R. Ahmad, "The digitization of agricultural industry – a systematic literature review on agriculture 4.0," *Smart Agric Technol*, vol. 2, p. 100042, 2022, doi:[10.1016/j.atech.2022.100042](https://doi.org/10.1016/j.atech.2022.100042).
2. W. Janssens, M. Pradhan, R. de Groot, E. Sidze, H. P. P. Donfouet, and A. Abajobir, "The short-term economic effects of COVID-19 on low-income households in rural Kenya: An analysis using weekly financial household data," *World Dev*, vol. 138, p. 105280, 2021, doi:[10.1016/j.worlddev.2020.105280](https://doi.org/10.1016/j.worlddev.2020.105280).
3. M.F. B. Alam, S. R. Tushar, S. M. Zaman, E. Gonzalez, A. Bari, and C. L. Karmaker, "Analysis of the drivers of Agriculture 4.0 implementation in the emerging economies: Implications towards sustainability and food security," *Green Technol Sustain*, vol. 1, p. 100021, 2023, doi:[10.1016/j.grets.2023.100021](https://doi.org/10.1016/j.grets.2023.100021).
4. A. A. Albeshier, "IoT in Health-care: Recent Advances in the Development of Smart Cyber-Physical Ubiquitous Environments," *IJCSNS Int J Comput Sci Netw Secur*, vol. 19, pp. 181–6, 2019.
5. V. Yeri, "IoT based Real Time Health Monitoring," *Proc. Second Int. Conf. Inven. Res. Comput. Appl.*, 2020, pp. 980–4.
6. M. U. Edodi, O. K. Ogidan, and A. Amusan, "Smart Irrigation System: A Water and Power Management Approach," *Proc 2022 IEEE Niger 4th Int Conf Disruptive Technol Sustain Dev NIGERCON 2022*, 2022, doi:[10.1109/NIGERCON54645.2022.9803183](https://doi.org/10.1109/NIGERCON54645.2022.9803183).
7. J. Chigwada, F. Mazunga, C. Nyamhere, V. Mazheke, and N. Taruvinga, "Remote poultry management system for small to medium scale producers using IoT," *Sci African*, vol. 18, p. e01398, 2022, doi:[10.1016/j.sciaf.2022.e01398](https://doi.org/10.1016/j.sciaf.2022.e01398).
8. A. Mottet and G. Tempio, "Global poultry production: Current state and future outlook and challenges," *Worlds Poult Sci J*, vol. 73, pp. 245–56, 2017, doi:[10.1017/S0043933917000071](https://doi.org/10.1017/S0043933917000071).
9. K. Ullah, V. Kumar Sharma, S. Dhingra, G. Braccio, M. Ahmad, and S. Sofia, "Assessing the lignocellulosic biomass resources potential in developing countries: A critical review," *Renew Sustain Energy Rev*, vol. 51, pp. 682–98, 2015, doi:[10.1016/j.rser.2015.06.044](https://doi.org/10.1016/j.rser.2015.06.044).
10. L. Domènech, "Improving irrigation access to combat food insecurity and undernutrition: A review," *Glob Food Sec*, vol. 6, pp. 24–33, 2015, doi:[10.1016/j.gfs.2015.09.001](https://doi.org/10.1016/j.gfs.2015.09.001).
11. M. Dhanaraju, P. Chenniappan, K. Ramalingam, S. Pazhanivelan, and R. Kaliaperumal, "Smart farming: Internet of things (IoT)-based sustainable agriculture," *Agric*, vol. 12, pp. 1–26, 2022, doi:[10.3390/agriculture12101745](https://doi.org/10.3390/agriculture12101745).
12. United Nations. THE 17 GOALS. UN Sustain Dev 2022. <https://sdgs.un.org/goals> accessed July 12th, 2024.
13. S. Munde, "IoT in Agriculture Market Research Report: Information By Component (Software System, Sensing, and Monitoring Systems, Fish Farming Systems, Smart Greenhouse Systems, Livestock Monitoring Systems, and Automation and Control Systems Services)," By Applicatio. Markert Res Futur, 2024.
14. K. Bounnady, P. Sibounnavong, K. Chanthavong, and S. Saypadith, "Smart crop cultivation monitoring system by using IoT," In: *2019 5th International Conference on Engineering, Applied Sciences and Technology (ICEAST)*, Vientiane, Laos, 2019 Jul 17–19, pp. 1–3.
15. G. R. Kumar, T. V. Gopal, V. Sridhar, and G. Nagendra, "Smart irrigation system," *Int J Pure Appl Math.*, vol. 119, no. 15, pp. 1155–68, 2018.

16. B. I. Bakare, T. C. Ewunonu, S. A. Bruce-Allison, and E. Eke, "Design and implementation of a smart irrigation system," *SSN (Online)*, pp. 2321–3795, 2022.
17. C. A. Ihendinihu and K. Inyama, "Development of smart irrigation system based on Internet of Things (IoT)," *Development*, vol. 9, no. 5, pp. 83–93, 2023.
18. N. M. Abdikadir, A. A. Hassan, H. O. Abdullahi, and R. A. Rashid, "Smart irrigation system," *Int J Electr Electron Eng*, vol. 10, no. 8, pp. 224–34, 2023.
19. S. Hosseininoorbin, S. Layeghy, B. Kusy, R. Jurdak, G. J. Bishop-Hurley, P. L. Greenwood, and M. Portmann, "Deep learning-based cattle behaviour classification using joint time-frequency data representation," *Computers and Electronics in Agriculture*, vol. 187, p. 106241, 2021.
20. L. Germani, V. Mecarelli, G. Baruffa, L. Rugini, and F. Frescura, "An IoT architecture for continuous livestock monitoring using LoRa LPWAN," *Electronics*, vol. 8, no. 12, p. 1435, 2019 Dec 1.
21. J. Magana, D. Gavojdian, Y. Menahem, T. Lazebnik, A. Zamansky, and A. Adams-Progar, "Machine learning approaches to predict and detect early-onset of digital dermatitis in dairy cows using sensor data," *Frontiers in Veterinary Science*, vol. 10, p. 1295430, 2023.
22. C. Nguyen, D. Wang, K. Von Richter, P. Valencia, F. A. Alvarenga, and G. Bishop-Hurley, "Video-based cattle identification and action recognition," In *2021 Digital Image Computing: Techniques and Applications (DICTA)*, 2021 Nov 29, pp. 01–05. IEEE.
23. W. Andrew, J. Gao, S. Mullan, N. Campbell, A. W. Dowsey, and T. Burghardt, "Visual identification of individual Holstein-Friesian cattle via deep metric learning," *Computers and Electronics in Agriculture*, vol. 185, p. 106133, 2021 Jun 1.
24. G. Gao, C. Wang, J. Wang, Y. Lv, Q. Li, Y. Ma, X. Zhang, Z. Li, and G. Chen, "CNN-Bi-LSTM: A complex environment-oriented cattle behaviour classification network based on the fusion of CNN and Bi-LSTM," *Sensors*, vol. 23, no. 18, p. 7714, 2023 Sep 6.
25. J. Judith, R. Tamilselvi, M. P. Beham, S. Lakshmi, A. Panthakkan, S. A. Mansoori, and H. A. Ahmad, "Remote Sensing Based Crop Health Classification Using NDVI and Fully Connected Neural Networks," *arXiv preprint arXiv:2504.10522*, 2025 Apr 11.
26. J. Qin, O. Monje, M. R. Nugent, J. R. Finn, A. E. O'Rourke, K. D. Wilson, R. F. Fritsche, I. Baek, D. E. Chan, and M. S. Kim, "A hyperspectral plant health monitoring system for space crop production," *Frontiers in Plant Science*, vol. 14, p. 1133505, 2023 Jul 4, doi:10.3389/fpls.2023.1133505.
27. Z. Wei and W. Fang, "UV-NDVI for real-time crop health monitoring in vertical farms," *Smart Agricultural Technology*, vol. 8, p. 100462, 2024 Aug 1, doi:10.1016/j.atech.2024.100462.
28. N. I. Hossain and S. Tabassum, "A hybrid multifunctional physicochemical sensor suite for continuous monitoring of crop health," *Scientific Reports*, vol. 13, no. 1, p. 9848, 2023 Jun 17, doi:10.1038/s41598-023-37041-z.
29. J. Y. Kim, "Open-source software for satellite-based crop health monitoring," *Journal of Biosystems Engineering*, vol. 49, no. 4, pp. 419–33, 2024 Dec, doi: 10.1007/s42853-024-00242-z.
30. G. Karuna, R. R. Kumar, P. Sanjeeva, P. Deepthi, H. Y. Saeed, V. Asha, L. Kansal, and P. Praveen, "Crop recommendation system and crop monitoring using IoT," *InE3S Web of Conferences*, 2024, vol. 507, p. 01063. EDP Sciences.
31. S. L. Shylaja, S. Fairouz, J. Venkatesh, D. Sunitha, R. P. Rao, and M. R. Prabhu, "IoT based crop monitoring scheme using smart device with machine learning methodology," In *Journal of Physics: Conference Series*, vol. 2027, no. 1, p. 012019, 2021 Sep 1. IOP Publishing.
32. G. C. Saha, M. R. Islam, M. M. Billah, H. I. Khan, R. C. Mat, M. M. Hossain, M. R. Hoque, E. S. Pramanik, and H. Saha, "IoT based smart agricultural crop monitoring in terms of temperature and moisture," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 11s, pp. 234–45, 2024.
33. H. Shahab, M. Naeem, M. Iqbal, M. Aqeel, and S. S. Ullah, "IoT-driven smart agricultural technology for real-time soil and crop optimization," *Smart Agricultural Technology*, vol. 10, p. 100847, 2025 Mar 1.
34. G. E. Okai, F. K. Minta, A. M. Osman, and A. Essilfie, "IoT-based Weather Monitoring System for Ghanaian Farmers," *International Journal of Computer Applications*, vol. 975, p. 8887.
35. T. Akilan and K. M. Baalamurugan, "Automated weather forecasting and field monitoring using GRU-CNN model along with IoT to support precision agriculture," *Expert systems with applications*, vol. 249, p. 123468, 2024 Sep 1.
36. Y. Song, J. Bi, and X. Wang, "Design and implementation of intelligent monitoring system for agricultural environment in IoT," *Internet of Things*, vol. 25, p. 101029, 2024 Apr 1, doi:10.1016/j.iot.2023.101029.
37. J. J. Dabrowski, A. Rahman, M. Li, Q. Shao, S. Bakar, A. Powell, and B. Henderson, "Quality control in weather monitoring with dynamic linear models," *arXiv preprint arXiv:2211.04528*, 2022 Nov 8, <https://arxiv.org/abs/2211.04528>.
38. C. J. Ezeofor, E. C. Okafor, and K. Akpado, "iot architecture for real time maize stem borers' detection and capturing in precision farming," *UNIZIK Journal of Engineering and Applied Sciences*, vol. 18, no. 1, pp. 381–92, 2021 Jun 1.
39. Y. Yuan, J. Sun, and Q. Zhang, "An enhanced deep learning model for effective crop pest and disease detection," *Journal of Imaging*, vol. 10, no. 11, p. 279, 2024 Nov 2, doi:10.3390/jimaging10110279.
40. S. Wang, P. Qi, W. Zhang, and X. He, "Development and application of an intelligent plant protection monitoring system," *Agronomy*, vol. 12, no. 5, p. 1046, 2022 Apr 27, <https://www.mdpi.com/2073-4395/12/5/1046#>.
41. J. Vardhan and K. S. Swetha, "Detection of healthy and diseased crops in drone captured images using deep learning," *arXiv preprint arXiv:2305.13490*, 2023 May 22, doi:10.48550/arXiv.2305.13490.
42. V. Impana, K. Vanishree, H. Kumar, and S. Atram, "Pests prediction and detection of disease spreading frequency in native crops using machine learning technique," *Int J Adv Res Inf Ideas Innov Technol*, vol. 8, no. 3, pp. 935–9, 2022. Available from: <https://www.ijarait.com/manuscripts/v8i3/V8I3-1453.pdf>
43. L. G. Tian, C. Liu, Y. Liu, M. Li, J. Y. Zhang, and H. L. Duan, "Research on plant diseases and insect pests identification based on CNN," In *IOP Conference Series: Earth and Environmental Science*, vol. 594, no. 1, p. 012009, 2020 Dec 1, doi: 10.1088/1755-1315/594/1/012009.
44. M. Li, S. Cheng, J. Cui, C. Li, Z. Li, C. Zhou, and C. Lv, "High-performance plant pest and disease detection based on model ensemble with inception module and cluster algorithm," *Plants*, vol. 12, no. 1, p. 200, 2023 Jan 3, doi:10.3390/plants12010200.

45. D. Gao, Q. Sun, B. Hu, and S. Zhang, "A framework for agricultural pest and disease monitoring based on internet-of-things and unmanned aerial vehicles," *Sensors*, vol. 20, no. 5, p. 1487, 2020 Mar 8, doi:[10.3390/s20051487](https://doi.org/10.3390/s20051487).
46. J. Wu, R. Tao, P. Zhao, N. F. Martin, and N. Hovakimyan, "Optimizing nitrogen management with deep reinforcement learning and crop simulations," In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2022, pp. 1712-1720.
47. C. Musanase, A. Vodacek, D. Hanyurwimfura, A. Uwitonze, and I. Kabandana, "Data-driven analysis and machine learning-based crop and fertilizer recommendation system for revolutionizing farming practices," *Agriculture*, vol. 13, no. 11, p. 2141, 2023, doi:[10.3390/agriculture13112141](https://doi.org/10.3390/agriculture13112141).
48. C. Kammerlander, V. Kolb, M. Luegmair, L. Scheermann, M. Schmailzl, M. Seufert, ... and T. Schön, "Machine learning models for soil parameter prediction based on satellite, weather, clay and yield data," 2025, *arXiv preprint arXiv:2503.22276*.
49. O. Folorunso, O. Ojo, M. Busari, M. Adebayo, J. Adejumo, D. Folorunso, ... and O. Olabanjo, "GeaGrow: A mobile tool for soil nutrient prediction and fertilizer optimization using artificial neural networks," *Frontiers in Sustainable Food Systems*, vol. 9, p. 1533423, 2025, doi:[10.3389/fsufs.2025.1533423](https://doi.org/10.3389/fsufs.2025.1533423).
50. U. Ikhlaiq and T. Kechadi, "Machine learning-based nutrient application's timeline recommendation for smart agriculture: a large-scale data mining approach," 2023, *arXiv preprint arXiv:2310.12052*.
51. L. Kalyani and B. P. Kolla, "Deep neural network-driven nitrogen fertilizer recommendation: A machine learning-based method for paddy soil and crop analysis using leaf imaging," *South Eastern European Journal of Public Health*, 2024.
52. S. Amerttet and G. Gebresenbet, "Forecasting the right crop nutrients for specific crops based on collected data using an artificial neural network (ANN)," *Machine Learning and Knowledge Extraction*, vol. 6, no. 3, pp. 1936-1952, 2024, doi:[10.3390/make6030095](https://doi.org/10.3390/make6030095).
53. J. Escorcia-Gutierrez, M. Gamarra, R. Soto-Diaz, M. Pérez, N. Madera, and R. F. Mansour, "Intelligent agricultural modelling of soil nutrients and pH classification using ensemble deep learning techniques," *Agriculture*, vol. 12, no. 7, p. 977, 2022, doi:[10.3390/agriculture12070977](https://doi.org/10.3390/agriculture12070977).
54. Y. J. Jeon, J. Y. Kim, K. S. Hwang, W. J. Cho, H. J. Kim, and D. H. Jung, "Machine learning-powered forecasting of climate conditions in smart greenhouse containing netted melons," *Agronomy*, vol. 14, no. 5, p. 1070, 2024, doi:[10.3390/agronomy14051070](https://doi.org/10.3390/agronomy14051070).
55. B. Alhnaity, S. Pearson, G. Leontidis, and S. Kollias, "Using deep learning to predict plant growth and yield in greenhouse environments," In: *International Symposium on Advanced Technologies and Management for Innovative Greenhouses: GreenSys2019*; 2019 Jun, vol. 1296, pp. 425–432.
56. T. Park, J. Lee, H. Oh, W. J. Yun, and K. W. Lee, "Optimizing indoor farm monitoring efficiency using UAV: Yield estimation in a GNSS-denied cherry tomato greenhouse," *arXiv preprint. 2025. arXiv:2505.00995*, doi:[10.48550/arXiv.2505.00995](https://doi.org/10.48550/arXiv.2505.00995).
57. J. Contreras-Castillo, J. A. Guerrero-Ibañez, P. C. Santana-Mancilla, and L. Anido-Rifon, "SAgric-IoT: An IoT-based platform and deep learning for greenhouse monitoring," *Applied Sciences*, vol. 13, no. 3, p. 1961, 2023, doi:[10.3390/app13031961](https://doi.org/10.3390/app13031961).
58. S. A. Magalhães, L. Castro, G. Moreira, F. N. Dos Santos, M. Cunha, J. Dias, and A. P. Moreira, "Evaluating the single-shot multibox detector and YOLO deep learning models for the detection of tomatoes in a greenhouse," *Sensors*, vol. 21, no. 10, p. 3569, 2021.
59. A. Elvanidi and N. Katsoulas, "Machine learning-based crop stress detection in greenhouses," *Plants*, vol. 12, no. 1, p. 52, 2022, doi:[10.3390/plants12010052](https://doi.org/10.3390/plants12010052).
60. X. Zhang, J. Bu, X. Zhou, and X. Wang, "Automatic pest identification system in the greenhouse based on deep learning and machine vision," *Frontiers in Plant Science*, vol. 14, p. 1255719, 2023, doi:[10.3389/fpls.2023.1255719](https://doi.org/10.3389/fpls.2023.1255719).
61. M. Kabir, P. Roy, S. S. N. Labonnya, A. I. Hussain, and M. F. Islam Design and implementation of a crop health monitoring system [dissertation]. Dhaka: Brac University; 2023.
62. T. Rohe, B. Böhm, M. Kölle, J. Stein, R. Müller, and C. Linnhoff-Popien, "Coconut palm tree counting on drone images with deep object detection and synthetic training data," *arXiv preprint arXiv:2412.11949* [Internet]. 2024 [cited 2025 May 10]. Available from: doi:[10.48550/arXiv.2412.11949](https://doi.org/10.48550/arXiv.2412.11949).
63. M. D. Bah, A. Hafiane, and R. Canals, "Deep learning with unsupervised data labelling for weed detection in line crops in UAV images," *Remote Sens.*, vol. 10, no. 11, p. 1690, 2018, doi:[10.3390/rs10111690](https://doi.org/10.3390/rs10111690).
64. Ž. Grbović, B. Ivošević, F. Franeta, and Ž. Milovac, "Unmanned aerial vehicle-based evaluation of pollination performance employing clustering image processing technique," *CABI Agric Biosci*, vol. 5, no. 1, p. 82, 2024, doi:[10.1186/s43170-024-00290-7](https://doi.org/10.1186/s43170-024-00290-7).
65. M. Kerkech, A. Hafiane, and R. Canals, "Vine disease detection in UAV multispectral images using optimized image registration and deep learning segmentation approach," *Comput Electron Agric.*, vol. 174, p. 105446, 2020, doi:[10.1016/j.compag.2020.105446](https://doi.org/10.1016/j.compag.2020.105446).
66. V. Mazzia, L. Comba, A. Khaliq, M. Chiaberge, and P. Gay, "UAV and machine learning based refinement of a satellite-driven vegetation index for precision agriculture," *Sensors*, vol. 20, no. 9, p. 2530, 2020, doi:[10.3390/s20092530](https://doi.org/10.3390/s20092530).
67. K. Vijayalakshmi, S. Al-Otaibi, L. Arya, M. A. Almahia, T. P. Anithaashri, S. S. Karthik, and R. Shishakly, "Smart agricultural-industrial crop-monitoring system using unmanned aerial vehicle-Internet of Things classification techniques," *Sustainability*, vol. 15, no. 14, p. 11242, 2023, doi:[10.3390/su151411242](https://doi.org/10.3390/su151411242).
68. S. Makam, B. K. Komatineni, S. S. Meena, and U. Meena, "Unmanned aerial vehicles (UAVs): an adoptable technology for precise and smart farming," *Discov Internet Things*, vol. 4, 2024, doi:[10.1007/s43926-024-00066-5](https://doi.org/10.1007/s43926-024-00066-5).
69. C. Bhuvaneshwari, G. Saranyadevi, R. Vani, and A. Manjunathan, "Development of High Yield Farming using IoT based UAV," *IOP Conf Ser Mater Sci Eng*, vol. 1055, p. 012007, 2021, doi:[10.1088/1757-899x/1055/1/012007](https://doi.org/10.1088/1757-899x/1055/1/012007).
70. X. Krasniqi and E. Hajrizi, "Science Direct Use of IoT Technology to Drive the Automotive Industry from Connected to Full Vehicles," *IFAC-PapersOnLine*, vol. 49, pp. 269–74, 2016, doi:[10.1016/j.ifacol.2016.11.078](https://doi.org/10.1016/j.ifacol.2016.11.078).
71. T. Zhivkov, E. I. Sklar, D. Botting, and S. Pearson, "5G on the farm: Evaluating wireless network capabilities and needs for agricultural robotics," *Machines*, vol. 11, pp. 1–26, 2023, doi:[10.3390/machines11121064](https://doi.org/10.3390/machines11121064).
72. O. Elijah, S. K. A. Rahim, M. J. Musa, Y. O. Salihu, M. J. Bello, and M. Y. Sani, "Development of LoRa-Sigfox IoT device for long distance applications," *Proc 2022 IEEE Niger 4th Int Conf Disruptive Technol Sustain Dev NIGERCON 2022* 2022, pp. 0–4, doi:[10.1109/NIGERCON54645.2022.9803173](https://doi.org/10.1109/NIGERCON54645.2022.9803173).
73. S. Madakam, R. Ramaswamy, and S. Tripathi, Internet of Things (IoT): A Literature Review, pp. 164–73, 2015.

74. R. Tang, N. K. Aridas, and M. S. Abu Talip, "Design of Wireless Sensor Network for Agricultural Greenhouse Based on Improved Zigbee Protocol," *Agric*, vol. 13, 2023, doi:[10.3390/agriculture13081518](https://doi.org/10.3390/agriculture13081518).
75. M. Singh, R. Kumar, D. Tandon, P. Sood, and M. Sharma, "Artificial intelligence and IoT based monitoring of poultry health: A review," *2020 IEEE Int. Conf. Commun. Networks Satell., IEEE*, 2020, pp. 50–4, doi:[10.1109/Comnetsat50391.2020.9328930](https://doi.org/10.1109/Comnetsat50391.2020.9328930).
76. H. M. Taleb, K. Mahrose, A. A. Abdel-Halim, H. Kasem, G. S. Ramadan, A. M. Fouad, *et al.*, "Using artificial intelligence to improve poultry productivity – a review," *Ann Anim Sci* 2024, doi:[10.2478/aoas-2024-0039](https://doi.org/10.2478/aoas-2024-0039).
77. P. Tokekar, J. Vander Hook, D. Mulla, and V. Isler, "Sensor planning for a symbiotic UAV and UGV system for precision agriculture," *IEEE Trans Robotics*, vol. 32, no. 6, pp. 1498–1511, 2016, doi:[10.1109/TRO.2016.2603528](https://doi.org/10.1109/TRO.2016.2603528).
78. X. Li, N. Ma, Y. Han, S. Yang, and S. Zheng, "AHPPEBot: Autonomous robot for tomato harvesting based on phenotyping and pose estimation," In: *2024 IEEE International Conference on Robotics and Automation (ICRA)*, Paris, France. IEEE, 2024 May 2024, pp. 18150–18156.
79. D. Guri, M. Lee, O. Kroemer, and G. Kantor, "Hefty: A modular reconfigurable robot for advancing robot manipulation in agriculture," *arXiv preprint arXiv:2402.18710*. 2024 Feb 28.
80. A. N. Sivakumar, S. Modi, M. V. Gasparino, C. Ellis, A. E. Velasquez, G. Chowdhary, and S. Gupta, "Learned visual navigation for under-canopy agricultural robots," *arXiv preprint arXiv:2107.02792*. 2021 Jul 6.
81. L. Cui, F. Le, X. Xue, T. Sun, and Y. Jiao, "Design and experiment of an agricultural field management robot and its navigation control system," *Agronomy*, vol. 14, no. 4, p. 654, 2024 Mar 23, doi:[10.3390/agronomy14040654](https://doi.org/10.3390/agronomy14040654).
82. D. Hall, F. Dayoub, J. Kulk, and C. McCool, "Towards unsupervised weed scouting for agricultural robotics," In: *2017 IEEE International Conference on Robotics and Automation (ICRA)*, Singapore. IEEE, 2017 May 2017, pp. 5223–5230, doi:[10.1109/ICRA.2017.7989612](https://doi.org/10.1109/ICRA.2017.7989612).
83. M. A. Basri and M. A. Adnan, "Autonomous agriculture robot for monitoring plant using internet of things," *Elektrika-Journal of Electrical Engineering*, vol. 21, no. 1, pp. 14–19, 2022, doi:[10.11113/elektrika.v21n1.336](https://doi.org/10.11113/elektrika.v21n1.336).
84. M. C. Manjunath and B. P. Palayyan, "An efficient crop yield prediction framework using hybrid machine learning model," *Revue d'Intelligence Artificielle*, vol. 37, no. 4, p. 1057, 2023, doi:[10.18280/ria.370428](https://doi.org/10.18280/ria.370428).
85. M. Kuradusenge, E. Hitimana, D. Hanyurwimfura, P. Rukundo, K. Mtonga, A. Mukasine, and A. Uwamahoro, "Crop yield prediction using machine learning models: Case of Irish potato and maize," *Agriculture*, vol. 13, no. 1, p. 225, 2023, doi:[10.3390/agriculture13010225](https://doi.org/10.3390/agriculture13010225).
86. A. Sarangi, S. K. Raula, S. Ghoshal, S. Kumar, C. S. Kumar, and N. Padhy, "Enhancing process control in agriculture: Leveraging machine learning for soil fertility assessment," *Engineering Proceedings*, vol. 67, no. 1, p. 31, 2024, doi:[10.3390/engproc2024067031](https://doi.org/10.3390/engproc2024067031).
87. K. Jhahharia, P. Mathur, S. Jain, and S. Nijhawan, "Crop yield prediction using machine learning and deep learning techniques," *Procedia Computer Science*, vol. 218, pp. 406–417, 2023, doi:[10.1016/j.procs.2023.01.023](https://doi.org/10.1016/j.procs.2023.01.023).
88. S. Sharma, G. K. Walia, K. Singh, V. Batra, A. K. Sekhon, A. Kumar, and D. Ghai, "Comparative analysis on crop yield forecasting using machine learning techniques," *Rural Sustainability Research*, vol. 52, no. 347, pp. 63–77, 2024, doi:[10.2478/plua-2024-0015](https://doi.org/10.2478/plua-2024-0015).
89. F. M. Talaat, "Crop yield prediction algorithm (CYPA) in precision agriculture based on IoT techniques and climate changes," *Neural Computing and Applications*, vol. 35, no. 23, pp. 17281–17292, 2023, doi:[10.1007/s00521-023-08619-5](https://doi.org/10.1007/s00521-023-08619-5).
90. Y. Huang, R. Srivastava, C. Ngo, J. Gao, J. Wu, and S. Chiao, "Data-driven soil analysis and evaluation for smart farming using machine learning approaches," *Agriculture*, vol. 13, no. 9, p. 1777, 2023, doi:[10.3390/agriculture13091777](https://doi.org/10.3390/agriculture13091777).
91. P. Patil, P. Athavale, M. Bothara, S. Tambolkar, and A. More, "Crop selection and yield prediction using machine learning approach," *Current Agriculture Research Journal*, vol. 11, no. 3, 2023 Dec 1, doi: [10.12944/CARJ.11.3.26](https://doi.org/10.12944/CARJ.11.3.26).
92. H. Khan and S. M. Ghosh, "Crop yield prediction from meteorological data using efficient machine learning model," *InProceedings of International Conference on Wireless Communication: ICWiCOM 2019*, Springer Singapore, 2020, pp. 565–574.
93. S. Amagai, Y. Fukuoka, T. Fujii, Y. Matsuzaki, H. Hosozawa, T. Ikegami, and R. Fukui, "Remote operation system for novice tractor drivers for situations where automatic driving is difficult," *J Field Robot.*, vol. 40, no. 6, pp. 1346–1362, 2023, doi: [10.1002/rob.22173](https://doi.org/10.1002/rob.22173).
94. P. Wang, M. Yue, L. Yang, X. Luo, J. He, Z. Man, and L. Hu, "Design and test of intelligent farm machinery operation control platform for unmanned farms," *Agronomy*, vol. 14, no. 4, p. 804, 2024, doi: [10.3390/agronomy14040804](https://doi.org/10.3390/agronomy14040804).
95. T. Liu, B. Zhang, Q. Tan, J. Zhou, S. Yu, Q. Zhu, and Y. Bian, "Immersive human-machine teleoperation framework for precision agriculture: Integrating UAV-based digital mapping and virtual reality control," *Comput Electron Agric.*, vol. 226, p. 109444, 2024, doi: [10.48550/arXiv.2308.07231](https://doi.org/10.48550/arXiv.2308.07231).
96. E. Kayacan, S. N. Young, J. M. Peschel, and G. Chowdhary, "High-precision control of tracked field robots in the presence of unknown traction coefficients," *J Field Robot.*, vol. 35, no. 7, pp. 1050–1062, 2018, doi: [10.1002/rob.21794](https://doi.org/10.1002/rob.21794).
97. Y. Li, Q. Cao, and F. Liu, "Design of control system for driverless tractor," *MATEC Web Conf.*, 2020, vol. 309, p. 04001, doi: [10.1051/mateconf/202030904001](https://doi.org/10.1051/mateconf/202030904001).
98. A. Ahmadi, M. Halstead, and C. McCool, "Towards autonomous visual navigation in arable fields," In: *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Kyoto, Japan, 2022 Oct 23–27, pp. 6585–6592. IEEE, doi: [10.48550/arXiv.2109.11936](https://doi.org/10.48550/arXiv.2109.11936).
99. D. Patel, M. Gandhi, H. Shankaranarayanan, and A. D. Darji, "Design of an autonomous agriculture robot for real-time weed detection using CNN," In: *Advances in VLSI and Embedded Systems: Select Proceedings of AVES 2021*, Singapore: Springer Nature Singapore, 2022, pp. 141–161, doi: [10.48550/arXiv.2211.12077](https://doi.org/10.48550/arXiv.2211.12077).
100. E. Kayacan, H. Ramon, and W. Saeys, "Robust tube-based decentralized nonlinear model predictive control of an autonomous tractor-trailer system," *IEEE/ASME Trans Mechatron.*, vol. 20, no. 1, pp. 447–56, 2014, doi:[10.1109/TMECH.2014.2334612](https://doi.org/10.1109/TMECH.2014.2334612).
101. E. Kayacan, H. Ramon, and W. Saeys, "Learning in centralized nonlinear model predictive control: Application to an autonomous tractor-trailer system," *IEEE Trans Control Syst Technol.*, vol. 23, no. 1, pp. 197–205, 2015, doi:[10.1109/TCST.2014.2321514](https://doi.org/10.1109/TCST.2014.2321514).
102. E. Lu, J. Xue, T. Chen, and S. Jiang, "Robust trajectory tracking control of an autonomous tractor-trailer considering model parameter uncertainties and disturbances," *Agriculture*, vol. 13, no. 4, p. 869, 2023, doi:[10.3390/agriculture13040869](https://doi.org/10.3390/agriculture13040869).

103. A. R. Conte, L. E. H. Morales, and L. H. Santana, "Path following control of autonomous tractor using non-linear guidance law," In: *Latin America Control Congress*, Cham: Springer, 2020, pp. 155–64.
104. Y. Li, Q. Cao, and F. Liu, "Design of control system for driverless tractor," In: *MATEC Web Conf.*, 2020, vol. 309, p. 04001, doi:[10.1051/mateconf/202030904001](https://doi.org/10.1051/mateconf/202030904001).
105. E. Kayacan, E. Kayacan, H. Ramon, O. Kaynak, and W. Saeys, "Towards agrobots: Trajectory control of an autonomous tractor using type-2 fuzzy logic controllers," *IEEE/ASME Trans Mechatron*, vol. 20, no. 1, pp. 287–98, 2015, doi:[10.1109/TMECH.2013.2291874](https://doi.org/10.1109/TMECH.2013.2291874).
106. T. Westny, B. Olofsson, and E. Frisk, "Uncertainties in robust planning and control of autonomous tractor-trailer vehicles," *arXiv preprint. 2023. arXiv:2311.14573*.
107. V. Ghodke and J. Madake, "Navigational path-planning for all-terrain autonomous agricultural robot," *arXiv preprint. 2021. arXiv:2109.02015*.
108. C. Zhang and Z. Liu, "Application of big data technology in agricultural Internet of Things," *J Sensors*, 2019, doi:[10.1177/1550147719881610](https://doi.org/10.1177/1550147719881610)
109. R. A. Dinesh, J. Shanmugam, and K. Biswas, "Integration of technology and nanoscience in precision agriculture and farming," In: *Contemporary Developments in Agricultural Cyber-Physical Systems. IGI Global*; 2023, pp. 150–170. <https://www.igi-global.com/chapter/integration-of-technology-and-nanoscience-in-precision-agriculture-and-farming/327602>
110. T. Samreen, S. Rasool, S. Kanwal, S. Riaz, Sidra-Tul-Muntaha, and M. Z. Nazir, "Role of nanotechnology in precision agriculture," *Environ Sci Proc.*, vol. 23, no. 1, p. 17, 2022, doi:[10.3390/environsciproc2022023017](https://doi.org/10.3390/environsciproc2022023017)
111. R. Anuja, J. Shanmugam, and K. Biswas, "Integration of technology and nanoscience in precision agriculture and farming," In: *Contemporary Developments in Agricultural Cyber-Physical Systems. IGI Global*; 2023, pp. 150–170. <https://www.igi-global.com/chapter/integration-of-technology-and-nanoscience-in-precision-agriculture-and-farming/327602>
112. S. S. Mukhopadhyay, "Nanotechnology in agriculture: prospects and constraints," *Nanotechnology, science and applications*, pp. 63–71, 2014 Aug 4.
113. D. Kaur and A. K. Virk, "Smart neck collar: IoT-based disease detection and health monitoring for dairy cows," *Discover Internet of Things*, vol. 5, p. 12, 2025.
114. H. Singh, N. Halder, B. Singh, J. Singh, S. Sharma, and Y. Shacham-Diamand, "Smart farming revolution: Portable and real-time soil nitrogen and phosphorus monitoring for sustainable agriculture," *Sensors*, vol. 23, no. 13, p. 5914, 2023, doi:[10.3390/s23135914](https://doi.org/10.3390/s23135914).
115. T. Sun, C. Lu, Z. Shi, M. Zou, P. Bi, X. Xu, and P. Xu, "PlantRing: A high-throughput wearable sensor system for decoding plant growth, water relations and innovating irrigation," *Plant Communications*. 2025, doi:[10.1016/j.xplc.2025.101322](https://doi.org/10.1016/j.xplc.2025.101322).
116. J. Abdulridha, A. Min, M. N. Rouse, S. Kianian, V. Isler, and C. Yang, "Evaluation of stem rust disease in wheat fields by drone hyperspectral imaging," *Sensors*, vol. 23, no. 8, p. 4154, 2023, doi:[10.3390/s23084154](https://doi.org/10.3390/s23084154).
117. R. Arablouei, G. J. Bishop-Hurley, N. Bagnall, and A. Ingham, "Cattle behaviour recognition from accelerometer data: leveraging in-situ cross-device model learning," *Comput Electron Agric.*, vol. 227, p. 109546, 2024, doi:[10.1016/j.compag.2024.109546](https://doi.org/10.1016/j.compag.2024.109546).
118. M. Thalheimer, "A leaf-mounted capacitance sensor for continuous monitoring of foliar transpiration and solar irradiance as an indicator of plant water status," *J Agric Eng.*, vol. 54, no. 1, 2023.
119. E. T. Bouali, M. R. Abid, E. M. Boufounas, T. A. Hamed, and D. Benhaddou, "Renewable energy integration into cloud & IoT-based smart agriculture," *IEEE Access*, vol. 10, pp. 1175–91, 2021 Dec 23.
120. A. U. Rehman, Y. Alamoudi, H. M. Khalid, A. Morchid, S. M. Mueen, and A. Y. Abdelaziz, "Smart agriculture technology: An integrated framework of renewable energy resources, IoT-based energy management, and precision robotics," *Cleaner Energy Systems*, vol. 9, p. 100132, 2024 Dec 1, doi:[10.1016/j.cles.2024.100132](https://doi.org/10.1016/j.cles.2024.100132)
121. M. S. Islam and G. K. Dey, "Precision agriculture: renewable energy based smart crop field monitoring and management system using WSN via IoT," In: *2019 International Conference on Sustainable Technologies for Industry 4.0 (STI)*. IEEE, 2019, pp. 1–6.
122. M. Rukhiran, C. Sutanthavibul, S. Boonsong, and P. Netinant, "IoT-based mushroom cultivation system with solar renewable energy integration: Assessing the sustainable impact of the yield and quality," *Sustainability*, vol. 15, no. 18, p. 13968, 2023 Sep 20, doi:[10.3390/su151813968](https://doi.org/10.3390/su151813968)
123. P. Palniladevi, T. Sabapathi, D. A. Kanth, and B. P. Kumar, "IoT based smart agriculture monitoring system using renewable energy sources," In: *2023 2nd International Conference on Vision Towards Emerging Trends in Communication and Networking Technologies (ViTECoN)*. IEEE, 2023, pp. 1–6, doi:[10.1109/ViTECoN58111.2023.10157010](https://doi.org/10.1109/ViTECoN58111.2023.10157010)
124. T. Nkanaunena and F. Chatola, "IoT-Enabled crop storage monitoring system," *I-manager's Journal on Communication Engineering and Systems*, vol. 11, no. 4, 2024, doi:[10.26634/jcom.11.4.20654](https://doi.org/10.26634/jcom.11.4.20654).
125. V. Sivathanu, M. K. R. Swami, and A. R. L. Padmaja, "Samhitha V. IoT-based smart food grain storage monitoring system for silos using google apps script," *Primer Scientific Engineering*, vol. 2, no. 5, 2023. <https://primerascientific.com/journals/psen/PSEN-02-050>
126. J. Lydia, R. Monisha, and R. Murugan, "Automated food grain monitoring system for warehouse using IOT," *Measurement: Sensors*, vol. 24, p. 100472, 2022 Dec 1, doi:[10.1016/j.measen.2022.100472](https://doi.org/10.1016/j.measen.2022.100472)
127. I. Viviane, E. Masabo, H. Joseph, M. Rene, and E. Bizuru, "IoT-based real-time crop drying and storage monitoring system," *Int J Distrib Sens Netw.*, vol. 2023, no. 1, p. 4803000, 2023, doi: [10.1155/2023/4803000](https://doi.org/10.1155/2023/4803000)
128. B. B. Zari, N. P. Samonte, M. B. Mendoza, S. C. Taruc, J. O. Evangelista, and E. C. Tuazon, "Automated IoT-based paddy grain monitoring system for enhanced storage efficiency and quality assurance," In: *2023 IEEE 9th Int Conf on Smart Instrumentation, Measurement and Applications (ICSIMA)*, 2023 Oct 17, pp. 220–4, doi:[10.1109/ICSIMA59853.2023.10373499](https://doi.org/10.1109/ICSIMA59853.2023.10373499)
129. A. Doltade, A. Kadam, S. Honmore, and S. Wagh, "Intelligent grain storage management system based on IoT," *Int J Sci Res (IJSR)*, vol. 8, no. 3, pp. 1749–52, 2019 Mar. [10.21275/ART20196559](https://doi.org/10.21275/ART20196559).
130. S. Nyamuryekung'e, "Transforming ranching: Precision livestock management in the Internet of Things era," *Rangelands*, vol. 46, pp. 13–22, 2024, doi:[10.1016/j.rala.2023.10.002](https://doi.org/10.1016/j.rala.2023.10.002).
131. T. Lin, M. Goldsworthy, S. Chavan, W. Liang, C. Maier, O. Ghannoum, et al., "A novel cover material improves cooling energy and fertigation efficiency for glasshouse eggplant

- production,” *Energy*, vol. 251, p. 123871, 2022, doi:[10.1016/j.energy.2022.123871](https://doi.org/10.1016/j.energy.2022.123871).
132. M. Muñoz, R. A. G. Morales, and J. A. Sánchez-Molina, “Comparative analysis of agricultural IoT systems: Case studies IoF2020 and CyberGreen,” *Internet of Things (Netherlands)*, vol. 27, p. 101261, 2024, doi:[10.1016/j.iot.2024.101261](https://doi.org/10.1016/j.iot.2024.101261).
 133. K. H. Y. Chung and P. Adriaens, “Blockchain technology for pay-for-outcome sustainable agriculture financing: implications for governance and transaction costs,” *Environ Res Commun*, vol. 6, 2024, doi:[10.1088/2515-7620/ad16f0](https://doi.org/10.1088/2515-7620/ad16f0).
 134. I. Viviane, E. Masabo, H. Joseph, M. Rene, and E. Bizuru, “IoT-Based Real-Time Crop Drying and Storage Monitoring System,” *Int J Distrib Sens Networks*, vol. 2023, pp. 1–11, 2023, doi:[10.1155/2023/4803000](https://doi.org/10.1155/2023/4803000).
 135. Myliquid, “The future of Zimbabwe’s Agricultural Industry powered by Internet of Things,” Myliquid 2016. w.myliquidhome.tech/articles/1552/the-future-of-zimbabwes-agricultural-industry-powered-by-internet-of-things.
 136. S. Kahindi, “Transforming agri-food systems in West Africa with digital technologies,” *Accel Incl Green Growth* 2024. <https://agridi.org/transforming-agri-food-systems-in-west-africa-with-digital-technologies/> (accessed June 12, 2024).
 137. A. Behura, S. Satpathy, S. N. Mohanty, and J. M. Chatterjee, “Internet of things: Basic concepts and decorum of smart services,” *Home Internet Things Its Appl. Chapter Internet Things Basic Concepts Decorum Smart Serv.*, pp. 3–36, 2022, doi:[10.1007/978-3-030-77528-5_1](https://doi.org/10.1007/978-3-030-77528-5_1).