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Review Paper

MODERN INFORMATION TECHNOLOGY IN SMART SUSTAINABLE AGRICULTURE (SSA): A REVIEW OF CURRENT TRENDS AND FUTURE DIRECTIONS

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ABSTRACT

The convergence of artificial intelligence (AI) and Internet of Things (IoT) in agriculture is poised to revolutionize the industry. By harnessing the power of AI and IoT, farmers can optimize crop yields, reduce waste, and promote sustainable farming practices. Recent years have witnessed a surge in the development of AI and IoT technologies tailored to agriculture, enabling farmers to monitor soil health, crop growth, and weather patterns in real time. The benefits of AI and IoT in agriculture are multifaceted. AI-powered systems can identify potential issues, such as pests, diseases, and nutrient deficiencies, allowing for early intervention and minimizing crop losses. IoT technologies provide farmers with actionable insights, enabling them to make informed decisions on planting, irrigation, and harvesting. Furthermore, the integration of AI and IoT in agriculture has the potential to transform the sector, enabling farmers to respond to environmental challenges more effectively and promoting sustainable farming practices. This review provides an overview of existing IoT/AI technologies adopted for Smart Sustainable Agriculture (SSA). The paper explores the current state of AI and IoT applications in agriculture engineering, identifying prominent applications and providing an IoT/AI architecture for a Smart Sustainable Agriculture platform.

Key words: *crop management, machine learning, smart agriculture, soil monitoring, sustainable farming, technology integration*

Abbreviations: AI - Artificial Intelligence; ANN - Artificial Neural Networks; BDA – Big Data Analytics; CC – Cloud computing; CNN - Convolutional Neural Networks; IaaS – Infrastructure as a Service; IoT- Internet of Things; IT – Information Technology; MC – Mobile Computing/ Mobile Cloud; ML – Machine Learning; PaaS – Platform as a Service; RFID – Radio Frequency Identification; SSA – Smart Sustainable Agriculture; SaaS – Software as a Service

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INTRODUCTION

The agricultural sector faces an unprecedented challenge in feeding a rapidly expanding global population, rendering conventional farming practices inadequate (Fess et al., 2011). As the world's population surges, innovative automation technologies are emerging to enhance food productivity and generate livelihoods for millions of people globally (Kakani et al., 2020). Farmers are turning to technologies like Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) to overcome challenges and improve farming efficiency (Sharma et al., 2022a). These technologies, known as "smart farming", enhance crop quality and quantity by making farming more connected and intelligent (Mohamed et al., 2021). The strategic application of AI and ML is revolutionizing agriculture, enabling farmers to optimize crop management, forecast weather conditions, and identify potential issues, resulting in enhanced yields and minimized waste (Javaid et al., 2023). By harnessing the power of technology, farmers are empowered to make informed decisions, maximize crop productivity, and adopt more sustainable practices, ultimately reducing their ecological footprint (Altieri et al., 2012).

The rapid advancement of technology has given rise to AI, a revolutionary field that allows humans to design and develop machines capable of simulating intelligent behavior (Pan, 2016). By leveraging the power of AI, machines can absorb knowledge from prior experiences and refine their actions to attain optimal results (Yahya and Yahya, 2018). Domains like Deep Learning, Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and Machine Learning enhance machine work and advance technology (Saleem et al., 2021). AI has penetrated various sectors, including medicine, education, finance, agriculture, and security (Rashid and Kausik, 2024). AI is machine learning, which involves feeding machines with data to perform tasks and solve problems (Shaikh et al., 2022). Machine learning has far-reaching implications, with diverse applications spanning data analytics, biometric identification, climate forecasting, and healthcare diagnostics, ultimately propelling the advancement of big data analytics and data-driven sciences (Sarker, 2021). The emergence of AI has spawned a range of innovative problem-solving approaches, encompassing Fuzzy Logic, ANN, Neuro-Fuzzy Logic, and Expert Systems, which collectively enable more effective and intelligent decision-making processes (Jha et al., 2019). ANN, inspired by the human brain, is a widely used method that involves training models with algorithms to perform tasks (Kujawa and Niedbała, 2021). The structural framework of ANN consists of a trio of interconnected layers: the input layer, which receives data; the hidden layer, where complex processing occurs; and the output layer, which generates the predicted results (Escamilla-García et al., 2020). AI and ML require a hardware-software interface, which is achieved through Embedded Systems (Redhu et al., 2022). The integration of AI and expert systems in agriculture has emerged as a burgeoning field of study, with nations such as South Korea, China, and those in North America making significant investments in agrotech innovations to revolutionize farming practices (Espinel et al., 2024). As a prominent agricultural producer, India is increasingly embracing automation technologies in farming to enhance productivity, streamline processes, and cater to the escalating domestic demand for food (Arora et al., 2022). Precision agriculture, also referred to as digital farming, leverages advanced computerized systems to meticulously monitor and analyze critical factors such as weed identification, crop forecasting, and yield optimization, thereby playing a vital role in contemporary agricultural practices (Mohyuddin et al., 2024). By 2050, the world's population is expected to swell to 10 billion, placing unprecedented pressure on the agricultural sector to substantially ramp up food production to meet the escalating demand (Lal, 2006; Pardey et al., 2014). To meet this demand, farmers are adopting technologies like IoT and AI to enhance productivity and reduce labor (Charania and Li, 2020). Digital agriculture is revolutionizing farming practices, enabling real-time analysis, precision farming, and sustainable production (Dayıoğlu and Turker, 2021). The success of this transformation is pivotal in alleviating the pressing issue of global food insecurity and guaranteeing a reliable, long-term food supply that meets the needs of a rapidly growing population (Pawlak and Kołodziejczak, 2020).

Sustainable agriculture is defined by its enduring resilience and harmonious relationship with the environment, promoting practices that not only ensure the health and prosperity of human communities but also preserve ecosystem balance and biodiversity (Pretty and Bharucha, 2014). It is financially practical, protects soil quality, conserves water, increases biodiversity, and ensures a healthy atmosphere (Rehman et al., 2022). The practice of sustainable farming serves as a cornerstone in the preservation of natural resources, the mitigation of biodiversity decline, and the minimization of greenhouse gas emissions, collectively fostering a more resilient ecosystem, a healthier planet, and a viable future for generations to come (Obaisi et al., 2022). This is achieved through efficient farming practices, including crop rotation, nutrient management, and water conservation, ultimately creating a safer and more sustainable world (Spiertz, 2009). The advancement of sustainable agriculture is being impeded by a confluence of pressing global challenges, including the escalating demands of a burgeoning population, the far-reaching consequences of climate change, the dwindling availability of natural resources, and the pervasive issues of food and water waste (Chartres and Noble, 2015). The imperative exists to devise groundbreaking technologies and

infrastructure capable of addressing the present needs while also anticipating and satisfying the demands of a rapidly evolving future (Khan et al., 2021). Throughout history, technological breakthroughs have been the catalyst for agricultural progress, evolving from basic implements to sophisticated robotics, and now, with the advent of intelligent technologies, the industry is on the cusp of a revolutionary transformation into a highly efficient, sustainable, and technologically advanced sector (Ayaz et al., 2019). As a vital element of sustainable agriculture, smart farming offers a paradigm-shifting solution to the labor-intensive and resource-draining aspects of conventional farming, streamlining and optimizing the entire agricultural value chain, from planting and harvesting to processing, logistics, and distribution (Kumar et al., 2024). Agriculture faces numerous vulnerabilities, including the exposure to toxic pesticides, adverse environmental factors, and pollutants, which collectively compromise the integrity of ecosystems, leading to the deterioration of soil health, air quality, and water purity (Zahoor and Mushtaq, 2023). The alarming erosion of biodiversity, a cornerstone of ecosystem resilience and vital for the sustenance of life on Earth, poses a significant threat, largely attributed to the detrimental impact of pollutants from waste emissions, fertilizers, and pesticides, which imperil the delicate balance of nature (Ogidi and Akpan, 2022). Furthermore, the release of greenhouse gases affects all living things, making it necessary to create a more favorable environment for life to thrive (Smith et al., 2008). The agricultural sector plays a vital role in India's economy, contributing substantially to the country's gross domestic product (GDP) with a share of 18%, while also serving as the primary source of livelihood for a majority of rural Indians, supporting approximately 57% of the rural population (Das et al., 2009). However, the number of farmers has declined over the years, and it is expected to drop to 25.7% by 2050 (Tiwari et al., 2019). Many young farmers are leaving agriculture due to increasing costs, poor productivity, and the lack of soil maintenance, opting for non-farming or better-paying jobs (Sick, 2014). It is essential to leverage technology, such as wireless connectivity, to create a digital platform for farmers, bridging the gap and transforming the agricultural landscape (Balyan et al., 2024). Not all land on earth is suitable for farming due to factors such as soil quality, terrain, temperature, and climate (Whittlesey, 1936). The existing agricultural land is also fragmented, leading to increased pressure on available arable land (Rey Benayas et al., 2007). To maximize crop production, it is essential to consider factors like soil quality, nutrient presence, irrigation, and pest resistance (Fageria, 2002). The strategic integration of IoT and AI in agriculture holds immense potential to revolutionize crop yields, amplify productivity, and minimize losses, thus effectively addressing the escalating global demand for food and ensuring a sustainable food future (Ben Ayed and Hanana, 2021).
For millennia, agriculture has been the backbone of human civilization, and now, with the world's population continuing to swell, the sector is confronting an unprecedented challenge: to substantially ramp up food production and ensure global food security for generations to come (Giller et al., 2021). In response to this pressing issue, the concept of smart agriculture has gained worldwide prominence as a pioneering initiative aimed at judiciously conserving resources, promoting eco-friendly practices, and fostering a sustainable agricultural paradigm that ensures a food-secure future (Steenwerth et al., 2014). The IoT is being harnessed to cultivate a more intelligent and interconnected agricultural ecosystem, yet the disparate and siloed nature of various agricultural processes presents a significant hurdle to overcome in realizing the full potential of IoT-driven agricultural innovation. This study aims to explore the existing IoT/AI technologies and propose a technical architecture for Smart Sustainable Agriculture (SSA) platforms, ultimately establishing a solution to advance smart agriculture globally.

Key Domains in Agriculture: Understanding the Complexities of Farming

The agricultural sector is a complex and dynamic industry, comprising diverse disciplines that intersect and interact to drive the efficiency, productivity, and sustainability of farming practices, ultimately contributing to the overall success and resilience of agricultural enterprises. These domains are interconnected and interdependent, requiring careful management and planning to achieve optimal results.

1. Human Resources: Effective management of human resources is essential in agriculture, as it impacts production, financial, and marketing decisions. To drive agricultural success, farmers must attract, develop, and retain top talent - individuals who possess the skills, passion, and communication expertise to excel in their roles, foster a positive work culture, and contribute to the farm's overall productivity and prosperity (Wilson, 2014).
2. Crops: Crops are the backbone of agriculture, providing food, feed, fiber, and oil. Understanding crop management, including planting, irrigation, and harvesting, is vital for optimal yields (El-Ramady, 2014).
3. Weather: Climate variability has a profound impact on agricultural productivity, with unfavorable weather events posing a significant threat to crop yields and farm profitability. As a result, the implementation of reliable weather monitoring and forecasting technologies has become increasingly crucial for farmers to anticipate, prepare for, and mitigate the risks associated with adverse weather conditions (Mase and Prokopy, 2014).
4. Soil: Maintaining optimal soil health is paramount for maximizing crop yields and quality. By leveraging IoT-enabled sensors, farmers can gain real-time insights into soil chemical properties, allowing them to precision-manage

fertilizer inputs, minimize waste, and optimize nutrient uptake for healthier, more resilient crops (Sivakumar et al., 2023).

5. Pests: The threat of pests poses a substantial risk to agricultural productivity and profitability, with potential consequences including widespread crop damage, livestock illness, and significant economic losses. Fortunately, the integration of IoT and AI technologies offers a powerful solution, enabling farmers to proactively monitor pest activity, predict infestations, and implement targeted control measures to mitigate damage and protect their assets (Reddy et al., 2024).

6. Fertilization: Optimal fertilization practices play a critical role in sustaining soil fertility, promoting healthy crop growth, and maximizing agricultural productivity. IoT sensors can help farmers optimize fertilizer application, reducing environmental harm and promoting sustainable agriculture (Getahun et al., 2024).

7. Agricultural Products: Agricultural products are derived from crops and livestock, providing food, clothing, and other essential items. Understanding the production and management of these products is vital for meeting global demand (Herrero et al., 2009).

8. Irrigation/Water: Effective water management is vital for agricultural sustainability, and innovative irrigation technologies can significantly mitigate water losses, ensuring that this precious resource is utilized optimally to support crop growth, while minimizing environmental impact (Obaideen et al., 2022).

9. Livestock: Livestock production is an integral part of agriculture, providing meat, dairy, and other essential products. Understanding animal husbandry and livestock management is vital for optimal production (Thornton, 2010).

10. Machines: Agricultural machinery is essential for efficient farming practices. Modern farm equipment can help reduce labor costs, improve productivity, and promote sustainable agriculture (Sims and Kienzle, 2017).

11. Fields: The health and productivity of agricultural fields are the backbone of farming operations, directly impacting crop yields and livestock performance. By harnessing the power of IoT technology to track and analyze field activities, farmers can unlock valuable insights, streamline operations, and implement data-driven strategies to boost efficiency, reduce waste, and drive sustainable growth (Ayaz et al., 2019).

METHODOLOGY

This review synthesizes the existing research on AI and IoT applications in agriculture. We conducted a comprehensive search of journal articles, conference papers, and book chapters indexed in IEEE Xplore, Clarivate, and Scopus, focusing on high-quality publications. Our methodology involved systematic search, screening, classification, and in-depth analysis of the relevant studies.

RESULTS AND DISCUSSION

Artificial Intelligence (AI)

The strategic integration of AI in agriculture is revolutionizing the sector by significantly enhancing crop yields, streamlining farming operations, and optimizing resource allocation, ultimately leading to substantial gains in productivity and efficiency (Javaid et al., 2023). By leveraging cutting-edge AI technologies, including machine learning, deep learning, and IoT, farmers are empowered to maintain a real-time oversight of their operations, facilitating data-driven decision-making on critical aspects such as crop optimization, soil health management, precision pest control, and other key factors influencing agricultural productivity (Kowalska and Ashraf, 2023). This results in higher yields, fewer losses, and more environmentally friendly farming practices. AI is revolutionizing various sectors, including agriculture, by replicating human cognitive abilities and streamlining processes through automation (Mishra and Mishra, 2023). AI-driven solutions, such as precision agriculture, optimize farming operations by enhancing efficiency and productivity through targeted support in critical tasks like precision irrigation, crop rotation planning, and predictive pest management (Sharma and Shivandu, 2024). Ultimately, AI holds the transformative power to revolutionize agriculture, driving global progress by simplifying intricate processes, amplifying productivity, and fostering a more sustainable and resilient food system (Bhat and Huang, 2021).

Over the past 50 years, AI has developed significantly and is now applied in various fields, including agriculture (Ruiz-Real et al., 2020). The agricultural sector is beset by a multitude of pressing issues, including the scourge of crop diseases, inadequate post-harvest storage, the complexities of pesticide regulation, and the perennial challenge of optimizing irrigation systems (Bouwer, 2000). AI has addressed these problems, providing feasible and reliable solutions.

For years, AI has been integrated into smart systems, striving to develop innovative machines that simplify and enhance daily life through intelligent automation (AlZubi and Galyna, 2023). The agricultural sector is witnessing a surge in AI-powered innovations aimed at boosting efficiency and addressing pressing concerns, including soil degradation, optimizing crop yields, and combating herbicide-resistant weeds (Ghatrehsamani et al., 2023). Agricultural AI solutions can be broadly classified into three key domains: autonomous farming robots that automate labor-intensive tasks such as harvesting, AI-powered crop and soil monitoring systems that leverage computer vision and deep learning to assess health and vigor, and predictive analytics platforms that utilize data-driven insights to forecast environmental influences on crop yields (Padhiary et al., 2024). AI technologies include See and Spray, Harvest CROO, and Plantix, which use machine learning to diagnose pests and soil defects (Giri et al., 2020). The integration of IoT and AI in agriculture yields a multitude of benefits, encompassing enhanced operational efficiency, reduced expenditures, improved profitability, and promotion of sustainable practices, as well as ensuring the safety of the food supply and safeguarding environmental integrity. Despite the potential benefits, the adoption of IoT and AI in agriculture is hindered by several obstacles, including prohibitively high upfront costs, the inherent complexity of these technologies, and a limited availability of suitable products tailored to agricultural needs (Ali et al., 2023). Effective deployment of smart agricultural technologies requires a multifaceted approach, encompassing comprehensive training for farmers to build their digital literacy, as well as rigorous testing and validation of IoT and AI applications to guarantee their efficacy, reliability, and suitability for agricultural use.

Revolutionizing Farming with Agricultural Robots

The advent of agricultural robots is revolutionizing the farming sector, yielding significant reductions in manual labor requirements while concurrently amplifying operational efficiency. These versatile robots are designed to multitask, seamlessly executing a range of functions that render them indispensable to agricultural operations. By harnessing the power of AI, agricultural robots can scrutinize and harvest crops with unprecedented precision, speed, and accuracy, far surpassing the capabilities of human labor and redefining the future of farming (Duckett et al., 2018; Lowenberg-DeBoer et al., 2020). Robots equipped with AI are programmed to meticulously monitor and preserve crop integrity, concurrently suppressing weed proliferation through targeted and precise interventions (Javaid et al., 2023). Furthermore, these AI-powered robots are capable of meticulously sorting and packaging produce in accordance with stringent quality benchmarks, thereby optimizing the post-harvest process, minimizing waste, and ensuring that only premium products reach the market (Bellon-Maurel et al., 2014). The synergistic fusion of AI and agriculture empowers farmers to strike a harmonious balance between maximizing crop productivity and preserving environmental sustainability, thereby fostering a more resilient, efficient, and eco-friendly food production system.

Artificial Neural Networks (ANN) in Agriculture

AI and IoT are transforming agriculture through predictive analytics and real-time monitoring, enabling informed decision-making and optimized resource allocation (Titirmare et al., 2024; Velusamy et al., 2021). The advent of automated farming is witnessing a profound transformation, driven by the integration of AI. AI-driven robots and drones are increasingly assuming responsibility for a range of labor-intensive tasks, including precision planting, selective pruning, and optimized harvesting, thereby significantly reducing labor expenditures, enhancing operational efficiency, and redefining the future of agricultural productivity (Agrawal and Arafat, 2024). Moreover, the synergy of IoT sensors and AI algorithms is revolutionizing precision irrigation, enabling farmers to optimize water application with unprecedented accuracy. By leveraging real-time soil moisture data, weather forecasts, and crop water requirements, AI-driven irrigation systems can minimize water waste, promote judicious water use, and foster a more sustainable and environmentally conscious approach to water resource management (Lakhiar et al., 2024). Additionally, advanced expert systems are being created to offer farmers tailored guidance on optimal crop management strategies, soil health optimization, and targeted pest control measures. These intelligent systems leverage machine learning algorithms, agricultural expertise, and real-time data to provide farmers with actionable, data-driven recommendations, empowering them to make informed decisions and refine their farming practices.

The integration of AI and the IoT in agriculture is further expanding into novel applications, including advanced soil moisture estimation. Sophisticated AI models are being employed to accurately predict soil hydration levels, thereby enabling farmers to refine irrigation protocols, minimize water waste, and optimize crop water utilization. Moreover, the synergistic combination of AI and IoT is also being leveraged for precision weed detection, where IoT sensors and AI-driven algorithms converge to identify weed presence, facilitating the targeted application of herbicides and significantly reducing chemical usage, ultimately promoting a more sustainable and environmentally conscious agricultural paradigm (Obaideen et al., 2022).

Internet of Things (IoT)

The Internet of Things (IoT) is a revolutionary technology that integrates smart devices into a unified network, leveraging a convergence of hardware and software infrastructure to enable seamless communication and data exchange between interconnected objects. At its core, the primary objective of IoT is to facilitate real-time monitoring, management, and automation of diverse environments and systems through the deployment of specialized device applications and interfaces (Ray, 2017). The IoT has experienced rapid proliferation across a broad spectrum of sectors, encompassing industrial automation, residential smart home systems, healthcare management, and urban infrastructure development, transforming the way we live, work, and interact (Chataut et al., 2023). Within the agricultural sector, IoT technologies are being harnessed to optimize the management of agricultural produce and supply chains, harnessing the power of real-time data analytics to facilitate precise searching, tracking, monitoring, and control, thereby enhancing operational efficiency, reducing waste, and driving informed decision-making (Rajabzadeh and Fatorachian, 2023).

To address the escalating global food demand, the integration of technology into agricultural practices has become imperative, as conventional farming methods are increasingly inadequate to meet the needs of a rapidly growing population (Lee, 2005). The IoT is poised to transform the agricultural landscape through automation, empowering everyday objects with the ability to sense, communicate, and respond to their surroundings, thereby fostering a more interconnected, efficient, and productive farming ecosystem (Kim et al., 2020). The synergistic convergence of IoT and AI has the potential to dramatically minimize manual intervention, enabling data-driven decision-making with unprecedented precision, speed, and reliability, thereby surpassing human capabilities in accuracy and efficiency (Javaid et al., 2023). Leveraging the power of AI, advanced systems can autonomously execute complex tasks that traditionally necessitate human cognitive abilities, including intuitive decision-making, nuanced language interpretation, and sophisticated problem-solving (Smith, 2018). The symbiotic union of IoT and AI is a crucial enabler of agricultural automation, rendering these two technologies inextricably linked and mutually reinforcing, much like the two sides of a coin, in the pursuit of optimized, high-yielding, and sustainable farming operations (Subeesh and Mehta, 2021). The proliferation of the IoT has resulted in an exponential surge in unstructured, real-time data, creating a pressing requirement for sophisticated data analytics capabilities to extract actionable insights and meaningful patterns from this vast, complex, and dynamic data landscape (Misra et al., 2020). The advent of AI algorithms, including Machine Learning and ANN, has revolutionized the analysis of complex data sets, unlocking the ability to distill actionable intelligence, inform strategic decision-making, and drive automation, thereby empowering organizations to harness the full potential of their data assets (Shaikh et al., 2022). Machine Learning algorithms possess the versatility to handle diverse data types, including both labeled and unlabeled datasets, whereas ANN exhibit exceptional proficiency in tackling intricate classification challenges, where nuanced pattern recognition and subtle distinction-making are paramount (Benos et al., 2021). The application of deep learning-based computer vision methodologies, notably CNN, has become increasingly prevalent in agricultural automation, facilitating the interpretation of intricate data patterns and empowering farmers to make more informed, precise, and timely decisions through enhanced data-driven insights (Akbar et al., 2024). CNNs have made significant advancements in image analysis, showcasing exceptional capabilities in tasks such as classification, segmentation, and object detection, owing to their robust ability to learn complex patterns and representations from visual data (Kamilaris and Prenafeta-Boldú, 2018). A CNN model is composed of a hierarchical architecture comprising multiple interconnected layers, specifically convolutional, pooling, and fully connected layers, that collaboratively operate to detect, extract, and process visual features from images, ultimately enabling accurate image classification and recognition (Liu et al., 2021b). In the convolutional layer, learnable kernels are applied to scan and detect local patterns, effectively extracting relevant features, whereas the pooling layer performs downsampling, strategically reducing spatial dimensions and parameter counts, thereby streamlining the network architecture and mitigating computational complexity (Barburiceanu et al., 2021). Following the convolutional and pooling stages, the extracted features are reshaped into a one-dimensional representation and input into a fully connected neural network, where a series of activation functions are applied to transform the outputs, ultimately yielding a probability distribution that enables classification and prediction (Mishra et al., 2020). Over the years, various deep learning architectures have been developed, such as AlexNet, VGGNet, and ResNet50, which have improved the performance and learning capacity of CNNs (Saleem et al., 2021). The synergistic integration of the IoT and AI is poised to transform the agricultural landscape, holding immense promise for augmenting crop yields, optimizing resource allocation, and alleviating the physical and manual burdens historically associated with farming, thereby enhancing the overall efficiency, productivity, and quality of life for agricultural workers.

Mobile Computing/Mobile Cloud (MC)

Mobile Cloud (MC) denotes an architectural paradigm wherein computational tasks and data repositories are relegated to remote servers, effectively offloading processing and storage responsibilities from resource-constrained mobile devices to the elastic, scalable infrastructure of the Cloud, thus granting MC applications unparalleled agility, adaptability, and responsiveness (Forcén-Muñoz et al., 2021). The proliferation of MC technology has had a profound influence on contemporary daily life, driven by its ubiquitous accessibility, affordability, and seamless communication capabilities, which have collectively empowered individuals to access a vast array of services, information, and connectivity on-demand, anytime, and anywhere (Vaezi et al., 2022). As a result, MC is now being used in every field, from education and healthcare to finance and entertainment. One of the domains where MC has made a substantial footprint is in the agricultural domain, where its innovative applications have revolutionized farming practices, enhanced productivity, and improved decision-making processes (Abualsaud et al., 2018). The integration of MC systems in agriculture has enabled the real-time collection and dissemination of critical data to farmers, furnishing them with actionable insights on crop health, weather patterns, and soil conditions. This data-driven approach empowers farmers to make informed, timely decisions, thereby minimizing crop losses, optimizing yields, and streamlining resource allocation. Furthermore, the convergence of MC and agriculture has given rise to cutting-edge practices such as precision agriculture and smart farming, which leverage advanced technologies to enhance the efficiency, sustainability, and productivity of farming operations (Kalyani and Collier, 2021). By harnessing the capabilities of MC, farmers can tap into a wealth of real-time data and actionable insights, allowing them to fine-tune their agricultural practices, streamline operations, and ultimately, boost their productivity and yields, thereby unlocking new levels of efficiency and competitiveness in the agricultural sector (Chandra et al., 2024). The use of automatic Radio Frequency Identification (RFID) systems is also becoming increasingly important in the agricultural sector. RFID technology is increasingly used in agriculture for real-time tracking and monitoring of products, enabling farmers to maintain visibility over inventory and supply chains from cultivation to storage. This technology is particularly valuable for managing high-value or perishable assets, such as livestock and crops, allowing farmers to minimize losses, optimize logistics, and enhance overall operational efficiency. Furthermore, RFID technology enables the secure storage and rapid retrieval of critical data on electronic tags, streamlining information management and decision-making processes (Ruiz-Garcia and Lunadei, 2011; Monarca et al., 2022). The application of MC and RFID technology is not limited to the agricultural sector. The strategic integration of MC and RFID technology has revolutionized the logistics landscape, empowering companies to achieve unprecedented levels of visibility, control, and precision in their supply chain operations. By harnessing the power of MC and RFID, organizations can track their products in real-time, mitigating the risks of loss, theft, and misplacement, while simultaneously streamlining their delivery processes, optimizing inventory management, and amplifying overall operational efficiency (Costa et al., 2013). The convergence of MC and RFID technology holds immense promise for transforming the fabric of modern life, empowering individuals, businesses, and societies to navigate the complexities of the digital age with greater agility, precision, and productivity. By harnessing the synergies of these technologies, we can unlock new frontiers of efficiency, innovation, and growth, ultimately redefining the way we interact, collaborate, and thrive in an increasingly interconnected world.

Cloud Computing (CC)

Cloud Computing (CC) has emerged as a transformative force in the realm of Information Technology (IT), transcending traditional boundaries to permeate diverse business domains and underpin a wide range of software applications and platforms. A key advantage of CC lies in its ability to provide seamless, on-demand access to scalable, high-performance computing resources and storage capacity via the Internet, while abstracting the intricacies of IT infrastructure management from end-users. This liberation from technological complexities enables users to concentrate on their primary objectives, unencumbered by the underlying infrastructure, and thereby amplify their productivity and efficiency (Gill et al., 2019). According to the National Institute of Standards and Technology (NIST), CC is formally defined as a paradigm that facilitates seamless, on-demand access to a shared, multifaceted pool of dynamically configurable computing resources - encompassing networks, servers, storage, applications, and services - which can be swiftly provisioned, scaled, and released with negligible managerial intervention or interaction with the service provider (Moura and Hutchison, 2016). This definition distills the essence of CC, emphasizing its core attributes: instantaneous availability, elastic scalability, and a dramatically reduced administrative burden, thereby underscoring the technology's capacity to provide flexible, efficient, and user-centric computing resources (Dahbur et al., 2011). The Cloud represents a sophisticated, large-scale virtualization paradigm, abstracting datacenter infrastructure into a geographically dispersed, interconnected network of resources, facilitated by high-speed networking. This enables the provisioning of a diverse array of virtualized services, spanning comprehensive infrastructures, discrete software applications, and specialized services, including high-performance computing and scalable storage solutions, all accessible through a flexible, consumption-based pricing model (Goldstein et al., 2022). CC can be conceptualized as a hierarchical, multi-layered architecture, comprising four distinct tiers: the hardware layer, which provides the foundational physical resources; the infrastructure layer, which virtualizes and manages these resources; the platform layer, which furnishes a software framework for application development and deployment; and the application layer, which delivers software applications and services to end-users (Patil et al., 2012). The four layers of CC form a hierarchical stack, each delivering a distinct category of service: the hardware layer serves as the foundational bedrock, supplying the physical infrastructure; the infrastructure layer builds upon this foundation, offering virtualized computing resources; the platform layer provides a comprehensive development and deployment environment, empowering application creation and hosting; and the application layer crowns the stack, delivering a broad spectrum of software applications and services to end-users (Patil et al., 2012). Cloud services can be categorized into three primary delivery models: Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS). These models provide a graduated spectrum of offerings, ranging from IaaS, which furnishes scalable, virtualized computing resources, to PaaS, which delivers a comprehensive development and deployment environment, and culminating in SaaS, which provides on-demand access to fully functional software applications, all accessible via the Internet (Mathur, 2024). CC, in conjunction with the IoT, has emerged as a highly efficacious paradigm for the storage, management, and analysis of agricultural data, offering a robust and scalable infrastructure for harnessing the vast amounts of data generated by modern farming practices (Channe et al., 2015). The integration of CC and the IoT in agriculture has given rise to a powerful data-driven paradigm, enabling the aggregation, storage, and analysis of vast amounts of data from disparate sources, including sensors, drones, and other connected devices. This synergy allows farmers to harness real-time insights, leveraging Cloud-based analytics and applications to inform data-driven decisions, optimize crop management, minimize waste, and ultimately, cultivate more resilient, productive, and sustainable agricultural ecosystems (Patil et al., 2012). By harnessing the capabilities of CC, agricultural stakeholders can tap into a rich reservoir of actionable insights, driving more informed decision-making, streamlined operations, and significant cost savings. As a result, CC has emerged as a transformative force in the agricultural sector, yielding substantial gains in productivity, efficiency, and competitiveness, while empowering farmers and agricultural enterprises to thrive in an increasingly complex and dynamic marketplace.

Big Data Analytics (BDA)

Big Data Analytics (BDA) encompasses the comprehensive methodology of collecting, aggregating, and scrutinizing vast, heterogeneous datasets sourced from diverse origins, including IoT sensors, online transactions, social media, and traditional business records, over an extended timeframe, to uncover hidden patterns, correlations, and insights (Jaber et al., 2022). BDA grapples with enormous, intricate datasets that exceed the processing and analytical capacities of conventional software and database architectures. The core objective of BDA is to ingest, store, and scrutinize this complex data, uncovering latent patterns, correlations, and relationships. To achieve this, BDA leverages cutting-edge methodologies, including machine learning algorithms, statistical modeling, data mining, and clustering techniques, alongside specialized technologies such as Hadoop, Spark, and other advanced analytics tools, to extract actionable insights and meaningful knowledge from these vast, complex datasets (Ikegwu et al., 2022). The integration of BDA in agriculture is a burgeoning domain, primarily concentrated on optimizing the agricultural supply chain. Through the examination of expansive datasets, agricultural stakeholders can garner actionable insights, facilitating data-driven decision-making, streamlined operations, and enhanced productivity. By harnessing the power of BDA, farmers and agricultural enterprises can mitigate production expenses, amplify crop yields, and cultivate more resilient and sustainable agricultural ecosystems (Yadav et al., 2022). Furthermore, BDA can be leveraged to scrutinize the characteristics of diverse soil types, enabling more precise categorization, tailored fertilization, and targeted improvement strategies, ultimately leading to optimized soil health, fertility, and productivity (Costa et al., 2023). Moreover, BDA can be harnessed to elevate crop forecasting and production, empowering farmers to make data-driven decisions regarding planting schedules, harvest timing, and irrigation strategies. This, in turn, can yield significant benefits, including enhanced operational efficiency, minimized waste, and bolstered profitability. Furthermore, the strategic integration of BDA in agriculture has the potential to transform the decision-making paradigm, enabling farmers and agricultural enterprises to transition from intuitive, experience-based choices to data-informed, precision-driven strategies, thereby unlocking new levels of productivity, sustainability, and competitiveness (Sadiku et al., 2020). Through the lens of BDA, farmers can uncover subtle trends and patterns that remain elusive through conventional methods. By scrutinizing vast datasets, farmers can distill valuable insights from weather patterns, soil conditions, and crop yields, informing planting and harvesting strategies with unprecedented precision. Moreover, BDA can be leveraged to analyze real-time data from sensors and

IoT devices, providing farmers with instantaneous visibility into crop health, soil moisture, and other yield-influencing factors.

Beyond optimizing crop yields, BDA can be a powerful catalyst for sustainable agricultural practices. By analyzing datasets related to soil health, water usage, and crop yields, farmers can pinpoint areas ripe for improvement, such as soil erosion hotspots or water-intensive zones. This data-driven approach enables farmers to adopt targeted conservation measures, minimizing environmental degradation while bolstering profitability.

Ultimately, the integration of BDA in agriculture heralds a paradigm shift in decision-making, sustainability, and profitability. By deciphering complex patterns within large datasets, farmers can cultivate a more informed, efficient, and environmentally conscious approach to agriculture, yielding tangible benefits for both their businesses and the planet (Getahun et al., 2024). As the agricultural sector becomes increasingly data-rich, the strategic application of BDA will emerge as a critical differentiator, empowering farmers to navigate the complexities of a rapidly evolving industry, capitalize on emerging opportunities, and maintain a competitive edge in a global marketplace where agility and adaptability are paramount.

Automation and Wireless System Networks in Agriculture

The agricultural landscape has undergone a profound metamorphosis with the emergence of cutting-edge technologies such as embedded intelligence, the IoT, and AI. Intelligent farming practices driven by embedded intelligence have significantly improved agricultural efficiency, productivity, and sustainability, paving the way for a more resilient and environmentally conscious food production system (Sharma et al., 2022b). Notably, innovators have created predictive systems that forecast grape disease outbreaks by leveraging sensor technologies and machine learning algorithms, enabling proactive measures to prevent crop damage. Furthermore, intelligent irrigation systems have been engineered to optimize water utilization, minimizing waste and promoting eco-friendly water stewardship. The integration of the IoT in agriculture has also witnessed remarkable growth, with IoT-enabled solutions transforming the way farmers monitor, manage, and optimize their crops, livestock, and resources, ultimately driving increased efficiency, productivity, and sustainability in agricultural practices (Adeyemi et al., 2017). The deployment of IoT-based systems has revolutionized agricultural field management by providing farmers with real-time insights, enabling data-driven decision-making. A notable illustration of this is the development of a cloud-based thermal imaging platform, which utilizes advanced analytics to assess soil hydration levels and provide precise irrigation recommendations, thereby optimizing water usage and promoting more efficient crop management practices (Ayaz et al., 2019). Furthermore, agricultural robots have been engineered to automate a range of labor-intensive tasks, including precision weeding, targeted spraying, and real-time moisture sensing, thereby significantly diminishing the reliance on manual labor and enhancing overall farm operational efficiency (Cheng et al., 2023). The application of machine learning algorithms in agriculture has yielded significant breakthroughs, notably in optimizing crop yields and minimizing waste. A prime example of this is the development of an advanced crop health monitoring system, which leverages machine learning-driven image recognition to identify pests and diseases, empowering farmers to initiate prompt and targeted interventions, thereby safeguarding crop integrity and promoting more resilient agricultural practices (Elbasi et al., 2023). Moreover, cutting-edge computer vision technologies have been harnessed to develop sophisticated weed detection systems, which utilize advanced image recognition capabilities to accurately differentiate between unwanted weeds and cultivated crops, thereby facilitating the automation of precise weeding operations and reducing the need for manual intervention (Fennimore et al., 2016). The convergence of IoT and AI technologies in agriculture has given rise to the creation of advanced decision support systems, designed to empower farmers with actionable intelligence. These intuitive systems furnish farmers with real-time data analytics and actionable insights, enabling them to make informed, data-driven decisions that optimize crop yields, reduce waste, and promote sustainable agricultural practices. A notable example of this is the development of a cloud-based decision support platform, which provides farmers with instantaneous access to critical agronomic data, including soil hydration levels, temperature fluctuations, and humidity readings, thereby facilitating precision farming and elevating agricultural productivity (Jayalakshmi and Gomathi, 2020). By harnessing real-time data and insights, farmers can fine-tune critical agricultural processes, including irrigation management, fertilizer optimization, and targeted pest control, ultimately culminating in enhanced crop productivity and minimized resource waste (Shah and Wu, 2019). Ultimately, the infusion of cutting-edge technologies like embedded intelligence, IoT, and AI has revolutionized the agricultural paradigm, empowering farmers to bolster crop yields, mitigate waste, and champion environmentally sustainable agricultural practices that ensure a more resilient and food-secure future.

Smart Sustainable Agriculture

The IoT is revolutionizing the agricultural landscape by harnessing the power of interconnected devices to boost crop productivity, minimize waste, and foster environmentally conscious practices. Innovative applications of IoT technology, such as intelligent greenhouses, precision agriculture, and real-time livestock monitoring, are exemplifying the vast potential of IoT to optimize agricultural operations, enhance sustainability, and drive business growth (Dhanaraju et al., 2022). Intelligent greenhouses leverage advanced sensor technologies to precisely calibrate temperature, illumination, and humidity levels, creating optimal growing conditions. Meanwhile, unmanned aerial vehicles (UAVs) and drones are being deployed to conduct aerial surveillance, assess crop vitality, identify potential pest threats, and scrutinize soil characteristics, providing farmers with actionable insights to inform data-driven decision-making (Aslan et al., 2022). Precision agriculture employs a convergence of advanced technologies, including sensors, autonomous machinery, and internet connectivity, to revolutionize irrigation management. By leveraging these innovations, farmers can precisely calibrate water application, minimize waste, and adopt environmentally responsible water stewardship practices, ultimately optimizing crop yields while conserving this vital resource (Adewusi et al., 2024).

AI is being increasingly integrated into agricultural practices to decipher complex soil characteristics, identify lucrative crop options, and predict yields with greater accuracy. By harnessing the analytical power of AI, farmers can make data-driven decisions, optimize crop selection, and refine yield forecasts, ultimately enhancing the efficiency and profitability of their operations (Javaid et al., 2023). Advanced sensors linked to the IoT generate instantaneous insights into weather patterns and climate conditions, empowering farmers to respond promptly and strategically to environmental factors, thereby optimizing crop care and maximizing yields (Thilakarathne et al., 2023). Autonomous agricultural robots, infused with AI, are revolutionizing farming practices by automating labor-intensive tasks, streamlining operations, and elevating crop quality. These intelligent machines are designed to precision-monitor crop health, suppress weed growth, and expedite the sorting and packaging of produce, thereby enhancing overall efficiency and productivity (Cheng et al., 2023).

SSA represents a visionary approach to farming, integrating IoT and AI technologies to foster environmentally conscious and efficient agricultural practices. This innovative paradigm encompasses precision farming, intelligent irrigation systems, and advanced greenhouses, all of which utilize IoT-enabled sensors to monitor soil moisture, temperature, and other critical factors, ensuring the precise application of water and optimizing crop yields while minimizing waste and environmental impact (Farooq et al., 2022). In addition, unmanned aerial vehicles (UAVs) and advanced sensor technologies are being leveraged in SSA to conduct aerial surveillance, assess crop vitality, identify potential pest threats, and scrutinize soil characteristics, providing farmers with real-time, data-driven insights to inform precision farming decisions and optimize crop management strategies (Mutanga et al., 2017).

The adoption of SSA is poised to transform the agricultural landscape, empowering farmers to optimize crop management and resource allocation through real-time data-driven insights. By harnessing the power of SSA, farmers can make informed, precision-based decisions, minimize waste, and adopt environmentally conscious practices, ultimately enhancing the long-term viability of their operations. Furthermore, the integration of automation and AI in SSA will alleviate the workload of farmers, while amplifying the efficiency, productivity, and resilience of their farming systems. As the global population continues to expand, the imperative for sustainable, efficient, and technologically advanced agricultural practices will intensify, rendering SSA a critical component of a food-secure future (Giller et al., 2021). SSA holds tremendous promise in mitigating this pressing issue, by catalyzing a paradigm shift towards eco-friendlier, efficient, and high-yielding farming methods. By harnessing the power of SSA, the global agricultural sector can rise to the challenge of satiating the world's burgeoning population, while concurrently minimizing the environmental footprint of farming practices and ensuring a more sustainable food future.

The advantages of SSA are multifaceted, encompassing enhanced crop productivity, optimized water usage, and the promotion of environmentally responsible practices. Additionally, SSA offers the potential to alleviate the labor burden on farmers, while concurrently amplifying the efficiency, productivity, and overall resilience of their agricultural operations, thereby yielding tangible economic and environmental benefits (Adenle et al., 2018). The strategic integration of IoT and AI technologies within SSA empowers farmers to make data-driven decisions, minimize waste, and adopt environmentally conscious practices, ultimately optimizing agricultural productivity, efficiency, and sustainability (Ngulube, 2025). In aggregate, SSA possesses the transformative potential to revolutionize the agricultural sector, fostering a paradigm shift towards environmentally conscious and efficient farming practices that can satiate the needs of a burgeoning global population while concurrently mitigating the ecological footprint of agricultural activities (Adenle et al., 2018).

Need for AI in Agriculture

AI is revolutionizing agriculture by enhancing productivity, sustainability, and efficiency. Through predictive analytics, crop monitoring, and data-driven decision-making, AI empowers farmers to optimize yields, mitigate risks, and reduce environmental impact (Nakalembe et al., 2021; Shaikh et al., 2022; Javaid et al., 2023). AI also benefits businesses by providing insights on demand forecasting, crop selection, and pricing trends (Kearney, 2010). By leveraging AI, farmers can overcome challenges, capitalize on opportunities, and contribute to a more sustainable food system (Javaid et al., 2023; Pretty, 2008; Liliane and Charles, 2020).

IoT in Agriculture: Benefits and Advantages

IoT in agriculture offers benefits like enhanced efficiency, reduced costs, and improved sustainability. The strategic deployment of IoT solutions enables data-driven decision-making and optimized resource allocation (Elijah et al., 2018; Monteiro et al., 2021). However, adoption challenges include high costs, technological complexities, and limited product availability. Addressing these barriers requires comprehensive training, rigorous testing, and tailored solutions (Javaid et al., 2023). A comprehensive review of the existing work highlights various tools, such as Farmapp, Growlink, and GreenIQ that are being implemented for a smart agriculture development (Table 1).

Table 1. IoT and AI in Action: Innovative Applications in Smart Agriculture (AlZubi and Galyna, 2023)

Sl. No.	Category	Tool/Company	Description
1	Agriculture machines/drones	CROO	A cutting-edge robotic system has been introduced, boasting the capability to harvest a vast 8-acre expanse of crops within a single day, thereby rendering the manual labor of 30 farmworkers obsolete. It uses advanced technology and AI to efficiently pick and pack crops, increasing productivity and reducing labor costs.
		See & Spray	A revolutionary agricultural robot, armed with advanced computer vision capabilities, has been engineered to pinpoint and eradicate weeds, as well as detect and treat diseased plants, providing farmers with a precise, efficient, and targeted crop protection solution.
		SkySquirrel	A drone system helps farmers improve crop yields and reduce costs by capturing images of their crops using computer vision. Following a predetermined flight path, the drone captures high-resolution images, which are subsequently transmitted to the Cloud for processing. Sophisticated algorithms then scrutinize the visual data, generating a comprehensive and actionable report on crop vitality and condition, enabling informed decision-making for optimal agricultural management.
2	Climate conditions Monitoring	allMETEO	A centralized platform orchestrates a network of IoT-enabled micro weather stations, furnishing instantaneous access to environmental data and generating dynamic, interactive weather visualizations. Additionally, the platform provides a versatile API, facilitating effortless integration and real-time data synchronization with existing agricultural systems, thereby empowering farmers to make informed, data-driven decisions and refine their crop management strategies.
		Pycno	A groundbreaking fusion of software and sensor technologies enables the seamless and continuous streaming of farm data directly to a smartphone, delivering instantaneous visibility into farm operations. The intuitive dashboard leverages cutting-edge phenological and disease modeling to track trends, evaluate risks, and forecast potential crop threats, empowering farmers to adopt proactive strategies and safeguard their harvests through data-driven decision-making.
		Smart Elements	A comprehensive portfolio of cutting-edge solutions revolutionizes farm productivity by automating labor-intensive monitoring tasks, harnessing the power of a sensor-driven network to gather critical data and produce actionable insights. These detailed analytics are seamlessly transmitted to a cloud-based platform, equipping farmers with the agility to respond promptly to emerging trends, make informed decisions, and drive operational efficiencies – ultimately minimizing labor expenditures and maximizing crop productivity.
3	Crop management	Arable	A sophisticated, integrated device simultaneously captures weather

			patterns and plant health metrics, transmitting this critical data to the Cloud for real-time accessibility. By delivering continuous, data-driven insights into plant stress, pest infestations, and disease outbreaks, farmers are empowered to adopt proactive, precision-based strategies, make informed decisions, and ultimately optimize crop yields through targeted interventions.
		Semios	A cutting-edge yield optimization platform enables farmers to monitor and respond to crop threats in real-time, leveraging a powerful fusion of on-farm sensors, vast data repositories, and advanced predictive analytics. By harnessing these insights, farmers can make data-driven decisions to fine-tune crop growth, mitigate losses, and boost productivity, ultimately cultivating a resilient and thriving agricultural operation that achieves long-term success and sustainability.
4	Crop and Soil Health Monitoring	Plantix	An AI-driven agricultural optimization tool leverages machine learning algorithms to streamline farming operations, effectively mitigating disease outbreaks and fostering the growth of premium crops. By delivering tailored insights, forecasting potential threats, and pinpointing areas for improvement, this innovative solution empowers farmers to boost crop yields, enhance profitability, and make data-informed decisions that drive sustainable agricultural success.
		Trace Genomics	A revolutionary soil monitoring platform employs cutting-edge genome sequencing techniques to decipher the genetic blueprint of soil microorganisms, cross-referencing the results with an extensive database to produce a comprehensive soil health assessment. By pinpointing subtle issues such as nutrient depletion and microbial symbiosis, farmers can implement precision interventions to restore soil vitality, optimize fertility, and promote a resilient and thriving ecosystem.
5	End-to-end farm management systems	Cropio	A cutting-edge decision support system harnesses the power of weather and satellite data analytics to inform precision fertilization and irrigation strategies, enabling farmers to optimize crop management and minimize environmental impact. By providing actionable insights and predictive forecasts, this innovative tool helps farmers strike a balance between reducing water and fertilizer consumption, boosting yields, and fostering sustainable agricultural practices that prioritize long-term ecosystem health.
		FarmLogs	A comprehensive agricultural management platform provides farmers with real-time field condition insights, enabling informed decision-making and optimized crop production planning. Additionally, the platform serves as a digital marketplace, bridging the gap between farmers and buyers, streamlining transactions, and enhancing the overall efficiency and profitability of agricultural operations.
6	Greenhouse automation	Farmapp	A sophisticated digital monitoring system tracks pest and disease activity, delivering actionable insights to farmers through mobile-based reports and a suite of data visualization tools, including satellite imaging, sanitary indices, thermal mapping, and graphical analyses, ultimately empowering farmers to make data-driven decisions and optimize their crop management strategies.
		GreenIQ	A cutting-edge, IoT-enabled agriculture solution empowers farmers to remotely monitor and control critical systems, such as irrigation and lighting, from anywhere, at any time. By seamlessly integrating IoT devices with automation platforms, this innovative system optimizes resource allocation, minimizes waste, and boosts crop

			productivity through automated, data-informed decision-making, ultimately revolutionizing the efficiency and sustainability of agricultural operations.
		Growlink	A comprehensive agricultural technology ecosystem integrates robust hardware and software components, enabling seamless wireless connectivity, precise data acquisition, and advanced analytics-driven optimization, to streamline farm operations, enhance decision-making, and drive productivity gains. By delivering real-time monitoring and intuitive data visualization, this innovative platform equips farmers with actionable insights, enabling them to adopt smarter, more informed approaches to farming and drive business success through data-driven decision-making.
7	livestock monitoring and management	Cowlar	A revolutionary, wearable neck collar utilizes cutting-edge technology to continuously track the vital signs of dairy livestock, including temperature, rumination patterns, and activity levels. This intelligent monitoring system enables early detection of health anomalies and provides precise alerts for optimal breeding windows, all within a rugged, solar-powered, and waterproof design that prioritizes animal welfare and minimizes maintenance requirements.
		SCR/Allflex	A sophisticated livestock monitoring platform harnesses the power of data analytics to deliver valuable insights on animal heat cycles, health status, and nutritional needs. By providing farmers with timely, actionable information, this innovative system enables data-driven decision-making, ultimately enhancing animal well-being, boosting productivity, and driving business profitability through optimized livestock management.
8	Predictive Analytics	aWhere	A groundbreaking aggrotech solution harnesses the power of precision weather forecasting and cutting-edge crop sustainability analysis to deliver data-driven intelligence, enabling farmers to make informed, strategic decisions and achieve optimal crop yields, while promoting environmentally responsible farming practices. By mitigating yield risks, minimizing losses, and fostering environmentally conscious practices, this innovative solution supports a more resilient, productive, and sustainable global food system.
		Farmshots	An advanced precision agriculture platform utilizes AI-powered analysis of satellite and drone imagery to identify early warnings of crop stress, disease, pests, and nutrient deficiencies. The system generates customized prescription maps to inform targeted interventions, while also providing actionable insights on farm performance through data-driven analytics. Additionally, the platform boasts interoperability with a wide range of agricultural software solutions, facilitating frictionless data exchange and synchronization, which in turn enables farmers to access a unified view of their operations, make data-driven decisions, and drive business success.

SSA-IoT/AI Platform Components

The SSA-IoT/AI platform consists of two main components:

1**. SSA Layers and AI/IoT Technologies**: This component is made up of several layers that work together to enable the platform's functionality (Elbasi et al., 2022). These layers include:

- **Infrastructure Layer:** This foundational layer comprises the physical computing infrastructure, data storage systems, and other essential hardware components that provide the underlying support for the platform's operations.

- **Intelligence and Data Analytics Layer:** This layer leverages AI and advanced data management capabilities to collect, process, and analyze the vast amounts of data generated by the platform, transforming it into actionable insights and informed decision-making tools.
- **Connectivity Layer:** This layer facilitates seamless communication, data exchange, and interoperability among the various components, devices, and systems within the platform, ensuring a cohesive and integrated architecture.
- **Cybersecurity Layer:** This critical layer provides robust protection and safeguards to ensure the confidentiality, integrity, and availability of data, as well as the secure transmission of information across the platform, defending against potential threats, vulnerabilities, and unauthorized access.
- **User Experience Layer:** This topmost layer serves as the primary interface for users, providing an intuitive, user-friendly, and engaging experience through various applications, tools, and services, allowing users to seamlessly interact with the platform and access its features and functionalities.
- **Perception Layer:** This foundational layer comprises a network of interconnected IoT devices, sensors, and actuators that detect, measure, and collect data from the physical world, providing real-time insights into environmental conditions, asset performance, and other critical factors.
- **Domain Knowledge Layer:** This layer encapsulates the specific expertise and knowledge related to the various domains within the Smart Farming or Agricultural ecosystem, including but not limited to crops, soil science, meteorology, and livestock management, providing a structured framework for integrating and applying domain-specific insights.

2. **Data Lifecycle within SSA Architecture:** This component encompasses the Data Intelligence process, which involves the systematic gathering, examination, and translation of data into actionable insights, facilitating informed decision-making and optimized outcomes within the platform (Mohapatra and Rath, 2022).

Data Processing and Analysis:

The platform enables on-site and off-site data sharing and processing. On-site processing occurs within the SSA environment, while off-site processing occurs in a remote data center (Alreshidi, 2019).

The data processing and analysis involve several steps (Tantalaki et al., 2019):

- Data collection: Data is aggregated from a diverse range of sources, encompassing IoT devices, sensors, and other data-generating entities, to create a comprehensive and unified data repository.
- Data analysis: The aggregated data undergoes sophisticated analysis through the application of advanced AI and machine learning (ML) techniques, uncovering hidden patterns, trends, and correlations.
- Data interpretation: The analyzed data is interpreted to provide insights and recommendations.
- Decision-making: The insights and recommendations are used to make informed decisions within the SSA environment.

The Security layer serves as the platform's first line of defense, safeguarding the confidentiality, integrity, and availability of sensitive data and communications. Leveraging a multi-faceted security approach, this layer deploys robust measures including end-to-end encryption, secure authentication protocols, and stringent access controls to prevent data breaches, unauthorized access, and malicious activities (Ali et al., 2019).

Harnessing Artificial Intelligence in Agriculture

AI is revolutionizing agriculture by optimizing crop performance, boosting yields, and enabling data-driven decisions through predictive analytics and machine learning (Javaid et al., 2023; Fuentes-Peñailillo et al., 2024; Domingues et al., 2022). By harnessing AI, farmers can enhance productivity, streamline operations, and adopt sustainable practices, ultimately ensuring a resilient and food-secure future (Javaid et al., 2023; Sharma and Shivandu, 2024). Moreover, AI can play a pivotal role in bridging the financial gap for farmers, leveraging data-driven insights to enhance their creditworthiness and unlock access to vital financial services, such as microloans, insurance, and savings programs, ultimately fostering greater economic stability and resilience (Table 2).

Table 2. Revolutionizing Farming: Exploring the Power of Artificial Intelligence (AI) in Agriculture

Sl. No.	Application	Description	References
1	Maximize Productivity, Minimize Effort	AI transforms agriculture by enabling better results with less effort. Smart farming combines traditional farming with technologies like IoT to improve product quality. Leveraging the power of AI, innovative agricultural	Kshetri, 2020; Lakshmi and Corbett, 2020; Joseph et al., 2021; Sahni et al., 2021; Sarkar et al.,

		solutions are being developed to identify and mitigate plant diseases, tailor seed and fertilizer applications to specific crop needs, and deliver expert guidance to farmers. These AI-driven tools are driving significant gains in crop productivity while promoting environmentally responsible farming methods, ultimately contributing to a more sustainable and food-secure future.	2022
2	Smarter Farming, Better Harvests: Unlocking Efficiency and Productivity for Farmers	The agricultural sector is undergoing a transformative shift, as AI converges with cutting-edge technologies like cognitive IoT, precision imaging, and autonomous robotics, empowering farmers to unlock unprecedented levels of productivity, optimize resource allocation, and cultivate more resilient, high-performing crops with reduced labor and environmental impact. The synergistic fusion of AI and advanced technologies is catalyzing a paradigm shift in agriculture, yielding a precision farming paradigm that harmonizes productivity, sustainability, and environmental stewardship. By providing farmers with actionable insights, this integrated approach enables data-driven decision-making, minimizes resource waste, and fosters the adoption of regenerative practices, ultimately culminating in a more agile, efficient, and environmentally conscious food system.	Fadziso, 2019; Sujatha et al., 2021; Mumtaz and Nazar, 2022; Alam et al., 2020
3	Assist food supply chain	The agricultural landscape has been transformed by the advent of AI, yielding unprecedented gains in crop yields, operational efficiency, and environmental sustainability. As the world grapples with pressing challenges like feeding a burgeoning global population, mitigating the impacts of climate change, and ensuring the integrity of the food supply, AI is emerging as a vital catalyst for innovation and resilience in the agriculture sector. Despite the promise of AI in agriculture, experts sound a note of caution regarding potential pitfalls. In response, researchers are diligently working to develop AI-powered solutions that prioritize sustainable farm management practices. Through rigorous study and analysis of AI's impact on global agricultural trade, production patterns, and resource utilization, scientists aim to foster a more resilient, sustainable, and equitable food system for the future.	Marinoudi et al., 2019; Salehin et al., 2020; Hadidi et al., 2021; Parasuraman et al., 2021
4	Crop & Soil Insights	The fusion of AI, drones, IoT sensors, and satellite imaging is transforming crop and soil surveillance, equipping farmers with precise insights to detect anomalies, pests, and diseases. Advanced algorithms and machine learning-powered platforms accelerate data interpretation, enabling targeted interventions, reduced chemical usage, and proactive pest management, ultimately driving eco-friendly agricultural practices and minimizing ecological footprint.	Weng et al., 2019; Marcu et al., 2019; Shelake et al., 2021; Maraveas et al., 2021; Qazi et al., 2022; Lowe et al., 2022
5	Detect anomalies and impurities	Machine learning algorithms precision-sort high-quality produce, while AI optimizes agricultural workflows, streamlines resources, and future-proofs food systems, thereby advancing sustainable farming methods and bolstering global food security.	Lu, 2019; Klerkx and Rose, 2020; Liu et al., 2020; Dakir et al., 2022
6	Detecting Microscopic	AI-driven agricultural innovations empower farmers with precision pest detection, automated crop monitoring, and	Patil & Kumar, 2020; Upadhyay and Gupta,

	Pests	data-informed decision-making. By integrating AI into farming practices, growers can optimize resource allocation, streamline operations, and anticipate market fluctuations. Furthermore, AI-enabled predictive analytics facilitate proactive weather risk management, minimize waste, and optimize supply chain logistics, culminating in a more agile, efficient, and environmentally conscious food ecosystem.	2021; Ashima et al., 2021; Sarkar et al., 2022; Singh and Jain, 2022
7	Detect soil defects	AI-driven agricultural intelligence harnesses data from IoT sensors, aerial imagery, and computer vision to pinpoint soil nutrient deficiencies and structural flaws, informing targeted soil remediation strategies. By processing vast datasets, AI generates precise predictive models, elevating agricultural precision and productivity. Moreover, AI-powered environmental monitoring encompasses water and air quality surveillance, as well as global disaster risk assessment, enabling proactive resource optimization, streamlined crop management, minimized waste, and the adoption of regenerative agricultural practices, ultimately fortifying global food security and sustainability.	Kodama and Hata, 2018; Wang, 2019; Sishodia et al., 2020; Widianto et al., 2022
8	Farm-Level Financial Planning	Technology tracks fund effectiveness at the farm level, replacing manual methods with real-time monitoring. AI drives automation and efficiency in agriculture, and its importance is growing with global trade expansion. Advances in AI technology have democratized access to data analytics, empowering farmers to make informed, sustainable choices and drive environmentally conscious agriculture forward.	Singhal et al., 2021; Khalifeh et al., 2021; Pallathadka et al., 2022; Sharma et al., 2022c
9	Drive predictive analytics	AI drives predictive analytics in agricultural sowing, enabling precise seeding, fertilization, and harvesting. This precision farming approach increases sustainability, producing more food with fewer resources, and is enhanced by modern technologies like autonomous systems and IoT, reducing labor and environmental impact.	Aitkenhead et al., 2003; Bhar et al., 2019; Chukkapalli et al., 2020; Costa et al., 2021
10	Precision Farming Techniques	AI-infused precision agriculture unlocks unprecedented efficiency gains, optimizing resource allocation, crop yields, and harvesting schedules. As global demand escalates, innovative technologies converge to propel agricultural productivity, paving the way for a sustainable, resource-conscious future where AI-driven farming ensures food security for generations to come.	Partel et al., 2019; Su, 2020; Fazal et al., 2022; Rozhkova and Rozhkov, 2022
11	Smart Crop Management	Autonomous farming assistants, leveraging AI and aerial robotics, enhance crop care through precision watering and data-driven forecasting, boosting agricultural productivity and resource stewardship. AI detects early problems, predicts weather conditions, and optimizes pesticide use, enhancing agricultural productivity and sustainability.	Ennouri et al., 2021; Sagan et al., 2021; Orchi et al., 2022; Chougule and Mashalkar, 2022; Saheb et al., 2022
12	Food Security Solutions	AI innovation in agriculture tackles pressing global challenges, mitigating food scarcity and minimizing losses attributed to environmental stressors. AI recommends optimal crops and seeds based on soil, weather, and market conditions, and provides customized advice to farmers. AI also helps smallholder farmers	Mir et al., 2021; Katyayan et al., 2021; Hyunjin and Sainan, 2021; Garrett et al., 2022

		access market information, reducing reliance on intermediaries. Furthermore, AI bolsters agricultural resilience through robust cybersecurity measures and informed decision-making, leveraging machine learning capabilities to distill insights from dynamic data streams, ultimately driving more efficient, adaptable, and eco-friendly farming practices.	
13	Help yield healthier crops	I-driven solutions empower farmers to optimize crop management, streamlining tasks such as pest control, soil monitoring, and data analysis, while also augmenting agricultural workforce efficiency and creating opportunities for skilled, tech-savvy professionals. AI combines with weather forecasts to determine ideal planting times and crop selection, reducing crop failure risks and business mistakes. Additionally, AI analyzes plant growth to produce disease-resistant crops and conducts soil analysis to identify nutrient deficiencies, promoting sustainable and efficient farming practices.	Orn et al., 2020; Zhang and Wang, 2020; Sharma et al., 2021; Monteiro and Barata, 2021
14	Identifying locations for sowing specific crops	AI-powered geospatial analysis of drone-captured imagery informs precision planting strategies, identifying ideal locations based on intricate factors such as topography, soil composition, and microclimates. AI also assesses seed quality, detects soil flaws and nutrient deficiencies, and aids in flora pattern analysis. Additionally, AI-powered tools use computer vision, robotics, and ML to control weeds, allowing farmers to target chemical sprays. This technology is advancing research in agriculture, food, and animal sciences, aiming to create accurate models that automate complex processes and improve decision-making.	Quinn et al., 2014; Bharti and Bhan, 2018; Fuentes et al., 2020; Sane and Sane, 2021
15	Identify wasteful resource consumption patterns.	AI systems analyze resource allocation and consumption, identifying areas for optimization and recommending alternatives. By leveraging preventive practices, such as monitoring livestock health and equipment performance, AI reduces costs and increases profitability. AI-driven sustainable agriculture practices optimize resource utilization, mitigating water depletion and soil degradation, while ensuring a harmonious balance between current needs and future resilience, for a more environmentally conscious and food-secure tomorrow.	Castro-Maldonado et al., 2018; Sánchez et al., 2020; Raman et al., 2021; Dora et al., 2022
16	Improve agricultural efficiency	Agribusinesses are harnessing the power of sensor fusion and AI-driven analytics to optimize crop yields, leveraging infrared imaging and drone surveillance to pinpoint prime harvests and monitor plant vitality. Meanwhile, AI's transformative impact on agriculture is ushering in a new era of data-driven farming, where farmers can tap into precise, location-specific weather forecasts and actionable insights derived from vast datasets. This synergy of technology and agriculture is redefining the industry's contours, unlocking unprecedented efficiency gains, and repositioning farmers for success in an increasingly complex and interconnected marketplace.	Vincent et al., 2019; O'Grady et al., 2019; Ghosh and Singh, 2020; Hyunjin, 2020
17	Informed Decision Making	The agricultural sector is undergoing a transformative shift, leveraging AI to amplify decision-making capabilities by harnessing insights from a vast array of	Hemming et al., 2019; Taberkit et al., 2021; Banthia and Chaudaki,

		data sources, including sensors, satellites, drones, and data loggers. By automating manual processes, precision farming empowered by AI provides actionable intelligence on weather trends, soil health, and optimal crop sequencing, leading to enhanced yields and improved resource allocation. Furthermore, AI-driven advisory systems offer farmers data-backed guidance on optimizing profitability, efficiency, and long-term sustainability, facilitating informed decisions that propel the adoption of environmentally conscious and resilient agricultural practices.	2022; Leal Filho et al., 2022
18	Maximize Harvest Potential	Leveraging AI in agriculture unlocks significant yield and productivity gains through advanced predictive modeling, real-time soil health monitoring, precision pest management, and insightful data-driven analysis. AI helps farmers produce healthier crops, maintain supply chains, and reduce costs. Machine learning algorithms decipher field data to decipher crop behavior, forecast desirable genetic attributes, and refine plant classification through nuanced analysis of leaf venation patterns and high-resolution aerial imagery, ultimately elevating agricultural productivity and environmental stewardship.	Kushkhova et al., 2019; Kun, 2020; Sujawat, and Chouhan, 2021; De Abreu and van Deventer, 2022
19	Increase farmer profitability	AI systems detect pests using satellite imagery, notifying farmers via smartphones to take action and save crops. AI also helps farmers grow more crops with less water, reducing resource costs and supporting drought-prone areas. While AI may automate some tasks, it's expected to create more jobs than it replaces, and human creativity will remain essential. Beyond agriculture, AI-driven technologies also extend to gardening, lawn maintenance, and landscaping, broadening its utility across diverse horticultural pursuits and solidifying its position as a versatile and indispensable resource.	Bestelmeyer et al., 2020; Sparrow et al., 2021; Liu et al., 2021a; Kumar et al., 2021a
20	Disease Detection	AI-assisted precision farming enables growers to pinpoint and eradicate invasive weeds, diagnose plant diseases, and implement targeted pest management strategies, optimizing crop health and minimizing environmental impact. It also forecasts optimal agronomic products, irrigation schedules, and nutrient application. AI automates harvesting, predicts ideal timing, and analyzes market demand, pricing, and crop readiness. With real-time predictions from drones and copters, farmers can optimize field management, creating feed maps and field maps to adjust water, fertilizer, and pesticide application, ultimately increasing efficiency and productivity.	Papadimitriou, 2012; Singh, 2018; Klerkx et al., 2019; Partel et al., 2021
21	Prediction of weather	AI-driven predictive analytics empowers farmers with actionable insights on weather patterns, soil quality, and crop status, facilitating proactive monitoring of crop well-being, swift issue detection, and data-driven decision-making to boost yields and mitigate losses. AI-powered security systems also monitor for potential threats, transforming farming operations with precision farming and predictive analytics.	Barenkamp, 2020; Al-bayati & Üstündağ, 2020; Rizvi et al., 2021; Singh and Kaur, 2022; Tzachor et al., 2022
22	Crop Insights	AI-driven predictive models forecast weather patterns and agricultural conditions, including soil fertility and water table levels, enabling farmers to optimize production	Tang et al., 2018; Vangala et al., 2020; Kawai and Mineno,

		planning, reduce uncertainty, and maximize yields. AI-enabled image recognition detects crop damage from pests and disasters, providing valuable insights to improve production. By leveraging IoT and AI-driven innovations, farmers can amplify food production and profitability while safeguarding the environment. Next-generation, AI-equipped robotics is being engineered to automate labor-intensive tasks such as precision weeding, harvesting, and packaging. Additionally, satellite imaging enables proactive threat detection, minimizing crop damage from wildlife and human activities, and ensuring a more resilient and sustainable agricultural ecosystem.	2020; Daoliang and Chang, 2020
23	Optimize Water Use	AI-powered agricultural platforms deliver tailored guidance to farmers on optimal water utilization, crop sequencing, and harvest planning, harnessing machine learning expertise and high-resolution satellite and drone imagery to assess crop resilience, forecast weather patterns, and inform data-driven decision-making. Precision farming uses accurate data to maximize yields, and AI software offers customized farm plans. The convergence of robotics, AI, and machine learning is revolutionizing gardening and agriculture, enabling automation, precise disease diagnosis, and optimized crop management. Digital agriculture empowers farmers with data-driven insights, facilitating informed decisions that balance economic viability, environmental stewardship, and regulatory compliance. This synergy of technology and sustainable practices is crucial for meeting the global food demands of a rapidly growing population, while preserving the planet's natural resources.	Hassan et al., 2016; Kaur, 2019; Zhang, 2020; Kumar et al., 2021b
24	Proper guidance	AI-driven solutions provide farmers with expert guidance on precision farming techniques, encompassing optimized crop sequencing, timely harvesting, efficient irrigation strategies, and targeted pest management. By enhancing decision-making agility and reducing operational expenditures, these AI-powered tools empower farmers to streamline their operations, boost productivity, and foster sustainable agricultural practices. Predictive analytics helps farmers analyze market demand, optimize irrigation and harvesting, and forecast prices. AI-powered precision agriculture detects plant diseases and pests through image analysis, enabling targeted pest control. AI robots also perform tasks like weed control and harvesting, increasing efficiency and productivity, and revolutionizing farming with automated and data-driven solutions.	Joseph et al., 2020; Hou and Wen, 2021; Galaz et al., 2021; Ganeshkumar et al., 2023
25	Self-driving tractors	The integration of AI, autonomous farming equipment, and IoT sensors can effectively mitigate labor gaps, enhance precision agriculture, and minimize operational expenses and inaccuracies, ultimately leading to increased efficiency, productivity, and profitability for farmers. Agricultural robots are also being used for tasks like harvesting and trimming, offering accuracy and efficiency. AI's advanced data analysis capabilities unlock actionable insights and predictive intelligence from intricate agricultural datasets, empowering businesses to make strategic, data-driven decisions, navigate industry	Jiayu et al., 2015; Santangeli et al., 2020; Songol et al., 2021; Sharma et al., 2022d

		nuances, and capitalize on emerging opportunities, thereby fueling growth, innovation, and competitiveness.	
26	Student studying regarding Agriculture	To leverage AI in agriculture, students should be educated on its applications, and collaboration among experts is necessary to develop relevant AI solutions. AI-powered monitoring systems track crop and soil vitality in real-time, identifying anomalies, detecting early warning signs of disease, and enabling proactive intervention, ultimately leading to enhanced crop yields, reduced waste, and the adoption of environmentally conscious farming methods.	Singh et al., 2020; Rathore, 2021; Chauhan et al., 2022; Ammar et al., 2022; Yaswanth Bhanu Murthy et al., 2022

Harvesting a Brighter Future: How AI is Transforming Agriculture

The advent of AI is ushering in a new era of innovation across multiple sectors, with agriculture being a key beneficiary. By harnessing AI capabilities, the agricultural industry is experiencing significant improvements in productivity, operational efficiency, and informed decision-making, revolutionizing traditional farming practices (Javaid et al., 2023). Deep learning, a subset of AI, enables data analysis and pattern recognition, similar to the human brain. This technology is being utilized for image processing, crop classification, and management (Dhanya et al., 2022). Next-generation agricultural robots, empowered by AI, are being engineered to execute vital tasks such as soil diagnostics, precision weed control, and optimized harvesting. These autonomous systems can operate with unprecedented scale, speed, and accuracy, far surpassing human capabilities. Additionally, industry leaders are allocating significant resources to develop advanced computer vision and deep learning capabilities, enabling the effective analysis of data captured by drones and software-driven platforms (Javaid et al., 2023). Advanced machine learning algorithms are being developed to forecast the effects of meteorological fluctuations and climate shifts on crop yields, enabling farmers and policymakers to proactively adapt to an increasingly unpredictable environment (Crane-Droesch, 2018). AI-driven agricultural solutions empower farmers with data-driven insights, offering tailored recommendations on irrigation strategies, crop sequencing, and nutrient optimization. By analyzing farm-specific data and external variables such as weather forecasts, these applications can also predict optimal crop selections. Furthermore, AI-powered systems can rapidly detect pest and disease outbreaks, enabling swift implementation of targeted control measures to minimize crop damage and promote sustainable farming practices (Adewusi et al., 2024). Moreover, AI facilitates farmers' access to a global network of suppliers, fostering expanded market opportunities and cross-border collaborations. As AI continues to transform the agricultural landscape, its integration is poised to revolutionize precision farming through the convergence of cutting-edge technologies, including computer vision, drone-enabled data capture, and real-time IoT alerts, ultimately enhancing the accuracy, efficiency, and sustainability of farming operations (Shaikh et al., 2022). Equipped with AI technology, drones are revolutionizing crop monitoring by rapidly identifying disease outbreaks with unparalleled precision, delivering farmers actionable, data-rich intelligence to inform timely and targeted interventions, and optimize crop health and yields. To ensure widespread adoption, it is essential to provide farmers with a suitable technological foundation and gradual exposure to AI features. AI technology also manages water distribution among crops without human intervention (Javaid et al., 2023). Advanced soil moisture and temperature sensors, integrated with embedded field components, continuously monitor and adjust to maintain the delicate balance of soil and water conditions essential for optimal plant growth. Meanwhile, the intelligent control system analyzes real-time data and makes informed, data-driven decisions on irrigation timing and frequency, adhering to predefined thresholds and ensuring precise, efficient water management (Kashyap and Kumar, 2021). Despite the vast potential of AI to transform agriculture, a significant knowledge gap persists, with many farms globally lacking exposure to cutting-edge machine learning innovations. Furthermore, the development and maintenance of AI-driven agricultural robots necessitate substantial investments in research and development, highlighting the need for sustained funding and support to bridge this technological divide and unlock AI's full potential in agriculture (Javaid et al., 2023). Undoubtedly, AI's impact on agriculture is profound, with far-reaching implications for data-driven decision making, precision farming techniques, and tailored advisory services, collectively holding the promise of enhanced productivity, efficiency, and sustainability in agricultural practices.

Limitations

The adoption of AI in agriculture is slowed by the lack of seamless, plug-and-play solutions that can be easily integrated into current farming infrastructures, highlighting the need for more intuitive, farmer-centric AI technologies that can be readily incorporated into traditional agricultural practices. Farmers' limited digital literacy and lack of time to explore AI solutions exacerbate this issue. To overcome this barrier, AI solutions must be designed to seamlessly integrate with the infrastructure and systems farmers already use. Despite AI's potential, its inherent constraints, such as limited functionality outside predetermined parameters, must be recognized. Furthermore, the shortage of technical expertise among farmers, particularly in rural areas, poses an additional barrier to AI adoption in agriculture. As AI technologies become more widespread and awareness grows, the agricultural sector may evolve towards semi-autonomous practices, harnessing AI to drive innovation. However, the development of reliable AI models is heavily contingent upon access to comprehensive and high-quality data, which can be difficult to obtain, especially in the context of crop-specific temporal data, highlighting the need for targeted data collection and curation initiatives to unlock AI's full potential in agriculture.

Future Scope

The agricultural landscape is on the cusp of a revolutionary shift, propelled by the accelerating evolution of AI innovations, which promise to reshape the future of farming and food production. AI is set to revolutionize the way farmers work, providing innovative solutions to pressing challenges such as pest control, weather prediction, and farm labor management. As AI technology advances, it will elevate farmers into precision agronomists, arming them with actionable, data-informed intelligence to fine-tune crop production, maximize yields, and minimize losses, thereby revolutionizing the art and science of farming. The development of AI-powered robots is also expected to transform farm work, enabling faster and more efficient crop harvesting, packing, and quality control. These robots will be trained to detect and manage weeds, overcoming labor shortages and improving overall crop quality. Additionally, AI-powered analytics will scrutinize satellite imagery and archival data to identify early warning signs of pest outbreaks, empowering farmers to implement targeted, preemptive strategies to mitigate potential damage and safeguard their crops.

The convergence of AI and agriculture will propel precision cultivation, enabling farmers to calibrate crop yields and quality while streamlining resource allocation. As AI technology continues to mature, it will assume a pivotal role in addressing pressing global food security concerns, exacerbated by the world's burgeoning population. To unlock the full transformative potential of AI in agriculture, however, it is imperative to prioritize inclusive access, ensuring that smallholder and remote farmers are also empowered to harness these innovations. By bridging the digital divide and amplifying the reach of AI-driven agricultural solutions, we can decentralize access to precision agriculture, catalyzing sustainable food systems worldwide. Ultimately, AI will emerge as a linchpin in optimizing agricultural resource utilization, efficiency, and productivity, while concurrently driving breakthroughs in horticultural R&D and propelling the future of sustainable agriculture.

CONCLUSION

The future prosperity of the agricultural sector is increasingly dependent on the strategic integration of cutting-edge computer technologies, including AI and the IoT. By synergizing these technologies with traditional farming methods, farmers can significantly enhance the efficiency, quality, and yield of their produce. This comprehensive study undertook an in-depth analysis of the existing AI and IoT technologies in agriculture, leveraging primary research journals to identify and categorize crucial aspects of intelligent and sustainable agriculture, encompassing crops, soil, weather, and irrigation management. The study's primary contribution lies in the development of a novel AI and IoT technology framework, tailored to support SSA. This framework seeks to address the inherent fragmentation of farming production processes, thereby optimizing the overall efficiency and paving the way for a more sustainable, technologically driven agricultural paradigm. The judicious integration of AI and IoT technologies has the potential to revolutionize the agricultural sector, driving significant improvements in productivity, efficiency, and sustainability. As the global agricultural industry continues to evolve, the adoption of these technologies will play an increasingly vital role in ensuring food security, mitigating environmental degradation, and promoting sustainable agricultural practices.

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