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Review Article

From Sensors to Insights: The Fusion of AI, Edge Computing, and Precision Agriculture

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ABSTRACT

Integrating artificial intelligence (AI), with edge computing, and precision agriculture is revolutionizing farming making it more resilient and sustainable. This article focuses on combine positive impact that the merger of these transformative technologies, can have in providing solutions for key challenges such as plant disease detection, resource optimization, and real-time decision-making. AI algorithms enables rapid and precise analysis of massive agricultural data allowing early disease detection and preventive measures to ensure plant health. Concurrently, edge computing gives the power of reduced latency with on spot data processing and solutions provision to the farmers, even in areas with limited coverage. The fusion of these technologies aligns with key UN sustainable development goals (SDGs), by optimizing the use of water, fertilizers, and pesticides, reducing environmental impacts, and mitigating climate change effects. However, the widespread adoption of AI and edge computing in agriculture is constrained by challenges such as hardware limitations, data collection, quality issues, and the need for technical expertise in particular cases. This review explores how these technologies are currently being used in agriculture, their pros, cons, and potential areas for further research and development. Encouraging interdisciplinary collaboration and continuous innovation will be crucial to overcome these challenges, ensuring that AI and edge computing play a central role in securing global food security and promoting climate-resilient farming.

Keywords: Artificial intelligence (AI), Edge computing, UNSDGs, Precision Agriculture, food security, climate sustainability

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INTRODUCTION

The incorporation of AI with edge computing, and precision agriculture is revolutionizing traditional farming approaches by introducing advanced tools for crop production management and plant disease detection (Sharma and Shivandu, 2024). This transition goes beyond technological advancement and represents a fundamental shift in how agriculture is approached, with sustainability at its core. With real-time monitoring systems, data analytics, and rapid decision-making, these technologies offer a comprehensive framework to increase productivity while reducing environmental impact. AI and edge computing are playing a transformative role in modern agriculture, offering unique opportunities to revolutionize traditional farming practices. AI-driven algorithms analyze big datasets in a much more precise and robust manner, leading to accurate predictions and diagnosis of crop health, pest infestations, and nutrient deficiencies. At the same time, edge computing processes data at the source, facilitating real-time insights and rapid responses to on-farm challenges (Sathya et al., 2024). Together, these technologies optimize resource allocation, enhance operational efficiency, and empower farmers with actionable intelligence, laying the foundation for resilient and sustainable agricultural ecosystems. Early disease detection is consider as one of the key challenges in agriculture sector, which directly impacts crop yields and overall food security (Strange and Scott, 2005; Sarfraz et al, 2023).

AI-based system, utilizing machine learning (ML) and computer vision (CV), have demonstrated the ability to identify diseases at initial stages. This early identification enable in time interventions, potentially reducing crop losses by up to 30% annually. Early detection systems also contribute to yield improvements, with studies indicating an increase of 20-25% higher outputs when disease is managed promptly. This approach highlights significance of integrating AI into agricultural systems for better results. Precision agriculture, powered by AI and edge computing, improves better utilization of resource resources, including water, fertilizers, and pesticides, leading to sustainable environment. Edge computing assists by processing vast amounts of data collected from IoT devices, sensors, and drones in real time and reduced latency, unlike traditional cloud computing, ensuring immediate responses to emerging issues such as pest infestations or nutrient deficiency (Johnraja et al., 2024). This capability is particularly valuable in resource-constrained areas where in timely decision-making makes a significance difference in ensuring crop health. Automated monitoring systems, powered by IoT devices and AI, have transformed the approach to crop health management. These systems provide continuous surveillance, significantly reducing the dependency on labor-intensive manual inspections. By leveraging several deep learning models such as convolutional neural networks (CNNs) and other AI models, these technologies can accurately diagnose diseases across various crops, regions, and climatic conditions. These models are designed to scale effectively, making them suitable for a wide range of agricultural environments (Ali et al, 2024). This adaptability is helping drive the adoption of smart farming practices across different farming communities.

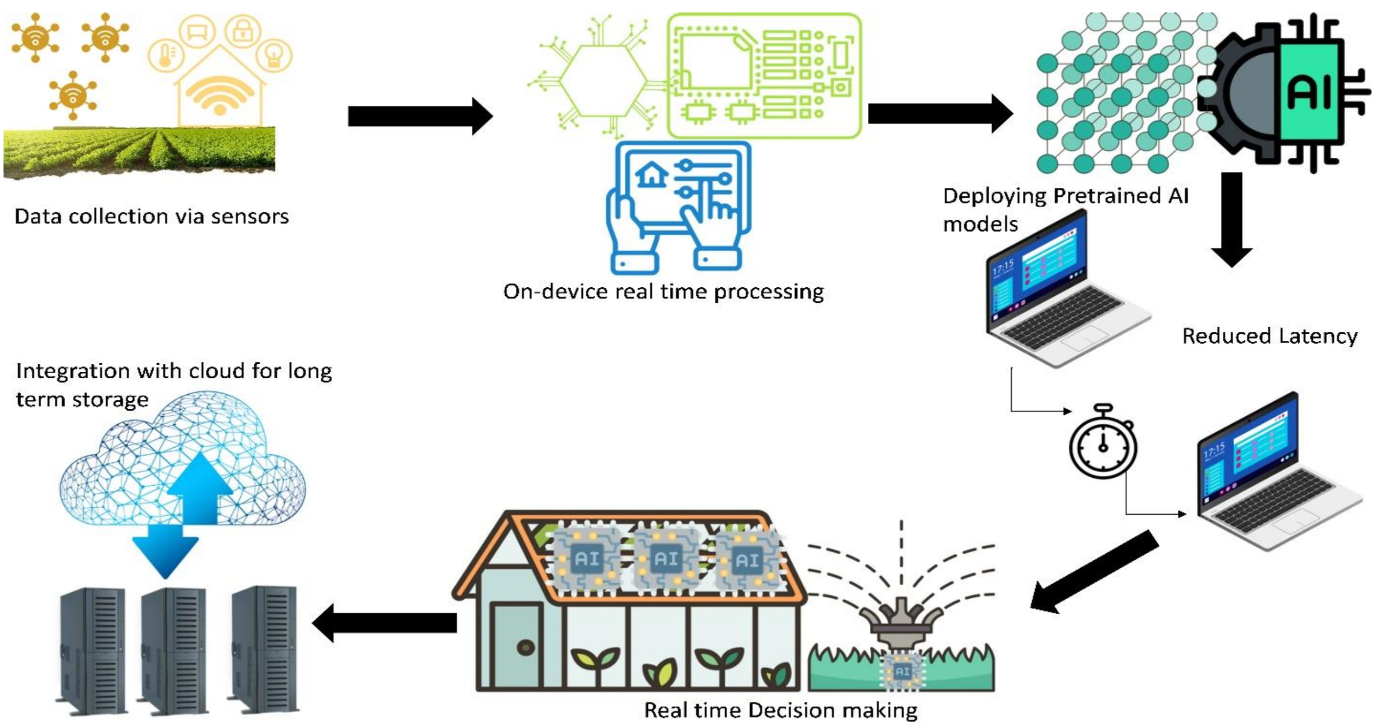

Figure 1. Working principle of edge computing is based on real time collection and processing of data, followed by decision making and solution deployment

Furthermore, the integration of AI with edge computing facilitates real-time decision-making at farm level. This localized processing capability enables farmers to address issues as they arise, rather than relying on delayed feedback from centralized systems (He et al., 2024). For example, data from soil moisture sensors can be analyzed instantly to optimize irrigation schedules for crops based on continuous data input, while drone based imaging can detect early signs of disease development, triggering immediate remedial actions. This agility in decision-making not only improves productivity outputs but also reduces wastage of critical agricultural resources. The fusion of these technologies also aligns with the broader goals of UN sustainable development goals (UNSDGs) by addressing tackling issues like food security, environmental conservation, and economic viability. By enabling precise and efficient farming practices, AI and edge computing contribute to reducing the agricultural sector's carbon footprint, mitigating the adverse effects of climate change.

In conclusion, the integration of AI, edge computing, and precision agriculture marks a significant leap forward in modern farming, reshaping the way crops are managed and agricultural challenges are addressed (El Alaoui et al., 2024). These synergistic technologies not only equip farmers with real-time, actionable insights for managing crop health and optimizing resources but also substitute long-term sustainability and resilience in agricultural systems. By allowing for early disease detection and smarter resource management, these technologies reduce the risks of crop loss and environmental harm. As they become more widely used, they have the potential to address major agricultural challenges, strengthen global food security, and promote sustainability for a growing population.

Technological Foundations

The integration of IoT devices and AI has ushered agriculture sector in to a new era, revolutionizing plant disease detection and crop management (Abdel-Basset et al., 2024). These advanced technologies provide farmers with powerful tools to monitor and analyze crop health in real-time, enabling early detection and prevention of diseases. This section delves into the technological foundations behind this transformation, focusing on IoT sensors for data acquisition and AI for analysis and decision-making.

Sensors and Data Acquisition

IoT sensors plays an important role in precision agriculture, by collecting important data on plants and surrounding environment. They provide continuous monitoring and real-time insights, forming the foundation of modern farming techniques, these sensors track key factors like soil moisture, temperature, humidity, and nutrient levels, helping farmers make informed decisions to improve crop health and productivity (Liang et al., 2023). These insights offer a more complete view of crop conditions, allowing farmers to better understand and manage their fields. These devices continuously monitor environmental factors in crop fields, and also extend to livestock management, tracking parameters like temperature, heart rate, and activity levels, leading to a reduced risk of delays in addressing potential issues (Hassan et al., 2023). Modern agricultural equipment, such as drones and tractor, are now available with built-in IoT sensors, allowing farmers to collect detailed data on crop health, field conditions, and pest activity. These advanced tools provide valuable insights that help optimize farming operations. The gathered data is then transmitted through reliable communication channels like Wi-Fi, Bluetooth, or cellular networks to centralized or edge servers for processing and analysis. (Yu et al., 2017). IoT sensors enable growers to make informed decisions regarding irrigation, fertilization, pest control, and other critical operations. By leveraging this data, farmers can optimize resource use and enhance crop productivity.

Artificial Intelligence in Agriculture

AI, complemented by ML algorithms, plays an instrumental role in transforming agricultural practices. By analyzing data from IoT sensors, AI delivers advanced insights and predictive capabilities, AI systems utilize diverse ML models reconfigured for agricultural applications, regression models predict crop yields based on historical and current data, Clustering models group plants with similar characteristics, aiding in targeted interventions, Bayesian models can provide accurate predictions for crop yield outputs and disease susceptibility, whereas Artificial neural networks (ANNs) helps in identification of complex patterns in agricultural datasets, enhancing the accuracy of predictions and diagnoses (Jabed and Murad, 2024). Deep learning models utilizing computer vision techniques process images for various applications; this include crop classification, disease detection, and disease classification (Jasim and Al-Tuwaijari, 2020). For instance, validation tests have shown that AI models achieve high accuracy rates, such as 97.09%, in detecting and classifying plant diseases (Jung et al., 2023). AI-based predictive models analyze historical data, weather patterns, and real-time field conditions to anticipate potential disease outbreaks. By providing early warnings, these models help farmers take preventive actions, reducing risks and improving crop management. Using data from IoT sensors and edge devices, AI algorithms generate instant insights and practical recommendations. For instance, monitoring soil moisture levels can lead to optimized irrigation schedules, while AI-powered analysis of drone imagery can identify early disease symptoms, allowing for precise and timely interventions. When it comes to scalability and accuracy, AI models—particularly convolutional neural networks (CNNs)—have shown impressive adaptability. They can effectively detect plant diseases across different crops, regions, and growing seasons, making them a powerful tool for modern agriculture worldwide.

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Edge Computing in Agriculture

Edge computing has emerged as crucial technological advancement in precision agriculture, offering rapid solutions for real-time data processing and localized decision-making (Karunathilake et al., 2023). Edge computing processes data right where it's collected, reducing delays, minimizing reliance on cloud services, and ensuring reliable operation even in areas with limited connectivity. This makes agricultural technology more efficient and responsive to real-time challenges. This technology combined with advanced sensor technologies, increases agricultural efficiency and sustainability through real-time insights, reduced latency, and improved resource management (Akhtar et al., 2021).

Edge computing facilitates immediate analysis of data collected from diverse sensors and farming equipment, significantly enhancing the decision-making process. By processing data locally, farmers gain access to actionable information into important parameters such as crop health, soil moisture levels, and machinery performance. This on-site data processing provides farmers with real-time insights, allowing them to track crop conditions and environmental factors instantly. With this timely information, they can make quick decisions and take necessary actions to improve yields and maintain healthy crops (Evans et al., 2017). The reduced dependence on remote data centers ensures that decisions, such as adjusting irrigation patterns, volumes or applying pesticides, can be made without delays. This resource allocation, enables growers to allocate water, fertilizers, and other inputs precisely, minimizing waste and improving productivity. Proximity of edge devices to data sources significantly reduces the time required for data transmission and analysis, making it possible to achieve latency as low as 5-10 milliseconds (Pang et al., 2021). The ultra-fast processing speed of edge computing is essential for time-sensitive farming activities. It enables real-time monitoring, ensures precision in agricultural operations, and enhances overall responsiveness. By handling data locally, it also reduces dependence on cloud services, offering both operational efficiency and cost-saving benefits. Optimization of smart farming machinery, such as drones and robotic tractors, to perform tasks with greater accuracy and efficiency. Integration of various data streams to develop a comprehensive understanding of farm ecosystems. Edge computing serves as a technological backbone for modern precision agriculture, bridging the gap between data collection and actionable insights (John et al., 2023). By addressing connectivity challenges, reducing latency, and minimizing dependency on centralized cloud systems, edge computing empowers farmers to make data-driven decisions in real time. This integration of edge computing with advanced sensors and AI-driven analytics not only enhances productivity but also fosters sustainable and resilient agricultural practices.

The integration of IoT sensors, edge computing, and AI in agriculture creates a complete system for detecting plant diseases and managing crops more effectively. This combination allows for real-time monitoring, data-driven insights, and smarter decision-making to improve overall farm productivity (Sharma and Shivandu, 2024). IoT sensors serve as the data acquisition layer, capturing a continuous stream of environmental and plant-specific metrics. This data is transmitted to AI systems, where it undergoes sophisticated analysis to extract actionable insights (Mushtaque and Technologies, 2024). By integrating these technologies, farmers can detect plant diseases at early stages, optimize resource usage, and improve overall crop yields. Moreover, this technological synergy addresses critical challenges such as pest outbreaks, soil degradation, and water scarcity. By providing a sustainable and efficient framework, IoT and AI-driven solutions enable precision agriculture to meet the demands of a growing global population. These advancements lay the groundwork for a resilient agricultural ecosystem capable of adapting to dynamic environmental conditions and ensuring food security in the face of global challenges.

APPLICATIONS IN PLANT DISEASE DETECTION

The combination of edge computing and ML in agriculture has transformed plant disease detection by providing real-time, precise, and cost-effective solutions. These innovations are especially valuable for farmers and researchers looking to improve crop health and make the most of their resources. By utilizing edge-AI pipelines and running machine learning models on edge devices, farming practices are becoming more efficient and environmentally friendly. Edge computing plays a crucial role in this transformation by allowing data to be processed right at the source, reducing reliance on cloud-based systems. This is particularly beneficial in agriculture, where real-time insights are essential for quick decision-making and timely interventions to protect crops and maximize yields (Sengupta et al., 2021). Devices equipped with image processing capabilities can instantly identify plant diseases. This on-site processing eliminates the latency associated with cloud-based systems and ensures immediate detection, enabling rapid responses to potential outbreaks. Edge-AI pipelines significantly reduce the volume of data transmitted to the cloud. Only the most relevant information is sent, minimizing network congestion and lowering associated costs. This efficiency is particularly beneficial in rural or remote farming areas with limited connectivity.

Integration of Machine Learning Models on Edge Devices

The deployment of ML models on edge devices has revolutionized real-time plant disease detection. These models are optimized for efficiency and accuracy while ensuring compatibility with the resource-constrained nature of edge devices.

Optimized convolutional neural networks (CNNs) like MobileNetV3Large have been specifically designed for deployment on edge devices. These streamlined architectures strike a balance between efficiency and accuracy, making them well-suited for environments with limited computing resources. Even with the constraints of edge devices, machine learning models running on these platforms have delivered impressive results. In fact, some edge-optimized models have demonstrated disease classification accuracy rates as high as 99.42%, highlighting their potential for real-world agricultural applications (Karim et al., 2024). ML models are tailored to run on energy-efficient hardware, such as the Nvidia Jetson Nano, this ultimately ensure that rapid disease detection systems remain accessible and cost-effective for small-scale and large-scale farmers alike (Biglari and Tang, 2023).

Real-world applications have demonstrated the effectiveness of edge-AI systems in detecting plant diseases directly in the field. These case studies highlight the tangible benefits of combining AI and edge computing in agriculture. For instance, in tomato leaf disease detection, researchers implemented a CNN-based approach that achieved an impressive accuracy of 98.99%, showcasing the potential of these technologies to enhance crop health monitoring and disease management (Gatla et al., 2024). This system's edge processing capability enable real-time identification, empowering farmers to implement timely treatments. A modified MobileNetV3Large model deployed on Nvidia Jetson Nano device demonstrated 99.42% accuracy in real-time grape disease detection (Ali et al., 2024; Karim et al., 2024). This precision enhances the ability to monitor and manage vineyard health effectively. Employing a hybrid attention mechanism, a prototype system achieved enhanced precision and real-time performance in identifying radish diseases. This development illustrates the potential of advanced algorithms in improving detection accuracy. An innovative edge AI application was developed to detect and spatially map diseases in citrus orchards (da Silva et al., 2023). This system provides spatial insights into disease spread, aiding targeted interventions and resource allocation.

The data processed by edge-AI systems not only facilitates real-time disease detection but also supports precision agriculture by enabling informed decision-making. Targeted Interventions: Immediate and localized treatment of detected diseases minimizes the use of pesticides, reducing environmental impact and cost. For example, studies suggest that such targeted approaches can lower pesticide usage by up to 20%, reduce water consumption by approximately 30% and fertilizer use by 20%, contributing to sustainable agricultural practices. Automated Monitoring via integration of edge-AI systems with autonomous machinery, such as drones and ground rovers, facilitates continuous disease surveillance and mapping. This automation reduces labor costs and improves the consistency of monitoring efforts. Approaches like Gradient-weighted Class Activation Mapping (Grad-CAM) enhance the interpretability of AI models (Karim et al., 2024). By visually highlighting affected areas, these systems enable precise targeting of treatment measures, further improving efficiency and efficacy. Edge-AI and integrated ML models are revolutionizing plant disease detection, offering real-time solutions that align with the goals of precision agriculture, by enabling rapid analysis, reducing latency, and optimizing resource management, these technologies address critical challenges such as early disease identification and sustainable resource utilization. The growing adoption of edge computing in agriculture underscores its potential to transform farming practices, ensuring food security and environmental sustainability in the face of global challenges.

BENEFITS AND CHALLENGES FOR AI-EDGE COMPUTING APPROACHES IN PRECISION AGRICULTURE

Benefits

The integration of Artificial Intelligence (AI) and edge computing in precision agriculture has catalyzed transformative advancements in crop management and plant disease detection. These technologies offer numerous advantages, ranging from real-time monitoring to improved scalability, fundamentally transforming the potential for sustainable farming. This subsection explores the primary benefits of utilizing edge-AI systems in agricultural applications.

Real-time Disease Monitoring and Response

One of the most important advantage of edge-AI systems is their ability to deliver real-time analysis and decision-making for plant disease detection. Traditional disease diagnosis methods often involve significant delays, relying on laboratory tests or centralized cloud systems, both of which consume time and resources. In contrast, edge devices equipped with AI models can analyze sensor data and images on-site, instantly identifying diseases as they occur. This real-time capability helps reduce the delay between when a disease first appears and when intervention occurs, significantly cutting down the potential for crop losses. For example, edge devices can analyze thermal images directly in the field to detect leaf diseases, all without needing to connect to the cloud (Da Silva et al., 2024). Real-time disease detection gives farmers the ability to take quick action, applying targeted treatments that make the best use of resources like pesticides and fertilizers. This proactive strategy not only makes interventions more effective but also helps avoid unnecessary chemical use. Such innovations are especially valuable when immediate responses are needed to prevent the spread of pathogens, which in turn protects crop yields and minimizes financial losses for farmers. Additionally, adopting edge computing offers significant cost savings over traditional cloud-based systems. These savings come from factors like reduced bandwidth usage, more efficient resource management, less reliance on cloud services, and greater scalability, which is particularly beneficial for smallholder farmers (Zamora-Izquierdo et al., 2019).

Scalability for Smallholder Farmers

Edge computing democratizes access to advanced agricultural technologies, making them feasible for farmers operating with limited resources. This scalability is particularly evident in form of, Affordable Hardware, Optimized AI Models, and Infrastructure Independence. Low-cost, energy-efficient devices, such as the Nvidia Jetson Nano, Google Coral, Intel NCS2, Agribotix Drone Edge Solutions, SenseGrass IOT, etc. are capable of running complex AI models tailored for agricultural applications (Zahid et al., {Adami, 2021 #29, {Adami, 2021 #29)}. These devices provide smallholder farmers with cutting-edge tools without the need for substantial investment. Lightweight models like MobileNetV3-small are tailored for use on edge devices with limited resources. Despite their small size, these models can achieve impressive accuracy rates, often surpassing 99%, in disease detection tasks. This optimization strikes a balance between strong performance and minimal computational needs. Edge solutions can operate efficiently without relying on advanced technological infrastructure, such as high-speed internet or centralized data centers. This independence makes them particularly suitable for deployment in remote or resource-limited areas, where traditional systems might not be feasible.

Enhanced Data Privacy and Security

The localized nature of edge computing confers significant advantages in terms of data privacy and security. In an era where data breaches and unauthorized data exploitation are growing concerns, edge-AI systems offer, Local Data Processing, Compliance with Privacy Regulations, Protection of Trade Secrets etc (Mahadevappa et al., 2024). By keeping data within the local network, edge computing reduces the need to transmit sensitive information to external servers. This containment minimizes exposure to cyber threats and protects proprietary farming data. Edge solutions allow farmers to retain control over their data, ensuring compliance with regional and international privacy standards. This control fosters trust among farmers, who may otherwise be hesitant to adopt digital technologies (Gupta et al., 2020). The ability to process and store data locally prevents unauthorized access to valuable crop information, safeguarding intellectual property and competitive advantages for agricultural enterprises.

Limitations

While the integration of AI and edge computing into precision agriculture presents transformative potential, several challenges and limitations hinder its widespread adoption and effective implementation. These obstacles span technical, economic, and operational domains and must be addressed to fully harness the benefits of these advanced technologies.

Hardware Constraints

The hardware employed in agricultural edge-AI systems often faces significant limitations in computational power, energy efficiency, and durability, particularly in remote and resource-constrained environments, Edge devices, such as the Nvidia Jetson Nano, are designed to run lightweight AI models efficiently. However, their limited processing capabilities make them unsuitable for more complex computations, such as real-time analysis of high-resolution multispectral or hyperspectral data (Biglari and Tang, 2023). This restricts their ability to process sophisticated tasks like plant disease diagnostics involving large datasets. Energy efficiency and power supply remain critical issues. In remote agricultural areas lacking reliable electricity, these constraints become significant barriers (McEnroe et al., 2022). Renewable energy solutions, such as solar-powered edge devices, are being explored but remain costly and require further development. Edge devices must withstand exposure to extreme weather, dust, and humidity. Designing rugged hardware that maintains optimal performance in such conditions adds to the complexity and cost of implementation (Rajak et al., 2023).

Data Quality and Model Robustness

The success of AI models in precision agriculture is highly dependent on the quality of input data and the robustness of the algorithms. Sensor data noise is a key challenge as agricultural data collected through sensors and imaging devices is often affected by noise, leading to inaccuracies in disease detection and crop monitoring (Vincent et al., 2019). Data preprocessing and advanced filtering techniques play a vital role in improving the reliability of agricultural data. AI models that are trained on specific datasets often face challenges when applied to different crops, regions, or seasons. For example, a model designed to detect tomato diseases in one area may not perform as well when used in another region with different environmental factors. Another significant challenge is the need for high-quality annotations. Many tasks, like crop health analysis and yield prediction, depend heavily on accurately annotated datasets, which can be a limiting factor in achieving reliable results (Dong et al., 2022). Achieving high-precision labeling is labor-intensive and expensive, yet essential for developing accurate AI tools.

Integration Challenges

The seamless integration of AI, edge computing, and existing agricultural systems is fraught with compatibility and interoperability issues (Zhang et al., 2020). The absence of standardized protocols among service providers can create challenges when trying to connect different components of precision agriculture systems. This often leads to fragmented systems that hinder the ability to make real-time decisions. The process of integrating edge devices with various communication technologies, such as fiber optics, satellite links, and cellular networks, can be trial-and-error, causing delays and driving up costs. Additionally, many farms still rely on traditional machinery and infrastructure that may not easily accommodate the integration of advanced edge devices. Retrofitting or upgrading these systems adds another layer of complexity to the process.

Adoption Barriers

Economic and technical challenges contribute significantly to the slow adoption of edge-AI technologies in agriculture, particularly in developing regions, limited internet connectivity in rural areas restricts the functionality of edge devices reliant on cloud-based support for updates or supplemental processing (El Jarroudi et al., 2024). Although edge computing reduces dependence on continuous internet access, occasional connectivity is still required for software updates and data synchronization. Lack of technical expertise to operate and maintain sophisticated AI-based systems is a key challenge as well, bridging this knowledge gap through training and support programs is essential but remains underdeveloped in many regions.

Overcoming these challenges requires collaborative efforts among researchers, technologists, policymakers, and the farming community. Several key initiatives including advancing hardware design, improving data quality, enhancing model generalizability and promoting training programs can assist in advancement and adaptabilities of Edge-AI systems ultimately moving closer to achieving sustainable and resilient farming practices.

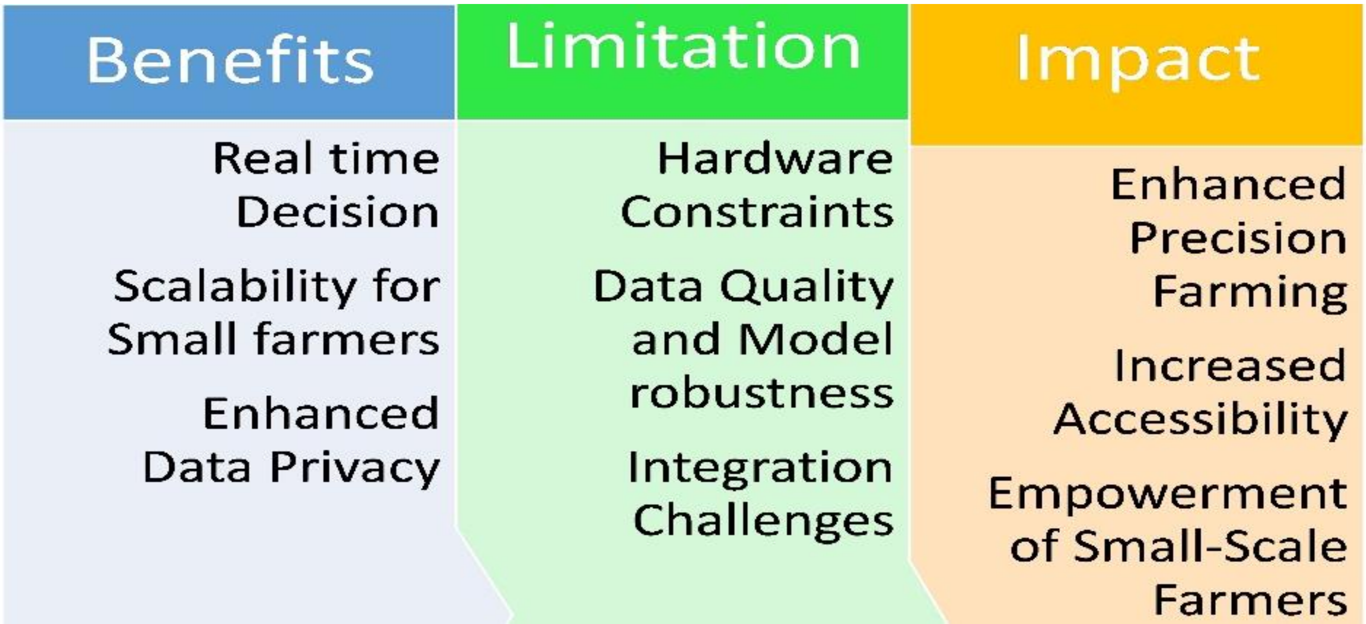

Figure 2. An overview of Edge AI in Agriculture: Benefits, Limitations, and Impacts on Sustainable Farming Practices.

FUTURE DIRECTIONS

The integration of artificial intelligence (AI) and edge computing in precision agriculture is paving the way for transformative advancements that promise to redefine farming practices. Emerging trends and innovations in this domain will likely enhance the efficiency, sustainability, and accessibility of agricultural operations, benefiting farmers, agronomists, and technology providers worldwide.

Advancements in Edge-AI Hardware

One of the most anticipated advancements in precision agriculture is the evolution of edge-AI hardware. Future edge devices are expected to feature more powerful and energy-efficient processors tailored to the specific needs of agricultural applications (Chen et al., 2018). These processors will enable the deployment of more advanced AI models directly on edge devices, leading to quicker and more precise real-time decision-making. Enhanced battery life and advanced power management systems will make it easier to deploy these devices in remote areas where access to reliable energy sources is scarce. Additionally, ruggedized edge devices designed to withstand extreme temperatures, humidity, and mechanical shocks will ensure their durability in the tough conditions often found in agricultural fields. These innovations will allow farmers to carry out complex tasks such as disease detection, yield forecasting, and environmental monitoring without relying on constant cloud connectivity, reducing both latency and operational costs.

Federated Learning for Decentralized AI Updates

Federated learning presents a revolutionary approach to enhancing the adaptability and accuracy of AI systems in precision agriculture. By enabling AI models to be updated across multiple farms without requiring the transfer of raw data, federated learning preserves data privacy and security. This decentralized methodology facilitates collaborative learning, where models learn from diverse agricultural conditions while respecting the confidentiality of individual farms (Sharma et al., 2023). The generalizability of AI models is significantly improved through federated learning, enabling them to perform effectively across varied crop types, regional conditions, and environmental challenges. The result is a suite of more robust AI tools capable of supporting farmers in diverse settings, fostering inclusivity in the adoption of advanced agricultural technologies.

Multi-Crop and Multi-Disease Frameworks

Future edge-AI systems are expected to move beyond single-crop or single-disease applications, evolving into comprehensive multi-crop and multi-disease frameworks. These systems will be designed to simultaneously monitor and analyze different crop types, identifying a wide array of plant diseases and pests. The integration of advanced sensors and AI algorithms will also enable edge devices to perform in-depth soil and environmental analyses. This holistic approach will provide actionable insights into the interplay between crops, soil health, and environmental conditions, optimizing resource management and boosting farm productivity. The adoption of such frameworks will allow farmers to implement tailored strategies for pest control, fertilization, irrigation, and disease prevention, enhancing both economic and environmental sustainability.

Blockchain for Secure Data Sharing

Blockchain technology is set to play a crucial role in ensuring the secure and transparent exchange of agricultural data. By providing a decentralized, tamper-proof ledger, blockchain will offer unmatched data integrity and trust. This system allows farmers and stakeholders to share information with confidence, knowing that the records are permanent and that access is controlled through smart contracts. These contracts will automate and enforce data-sharing agreements, facilitating smooth collaboration between farmers, researchers, and tech providers. Early studies that integrate blockchain with precision agriculture have shown encouraging results, with methods achieving up to 98.31% accuracy in secure data transactions (Kalimuthu et al., 2024). This technological convergence will address critical issues of data security, privacy, and ownership, creating a trusted ecosystem for precision agriculture.

The future of precision agriculture lies in the synergistic combination of advancements in edge computing, AI, federated learning, blockchain, and multi-functional frameworks. These innovations will not only enable real-time, accurate, and secure agricultural operations but also provide scalable and sustainable solutions to address the growing global challenges of food security and environmental conservation. As research and development efforts continue to expand, these technologies hold the promise of transforming agriculture into a more efficient, equitable, and environmentally responsible industry.

CONCLUSION

The integration of artificial intelligence (AI), edge computing, and advanced sensor technologies is reshaping modern agriculture, paving the way for more sustainable, efficient, and resilient farming practices. These cutting-edge solutions have revolutionized how farmers monitor their crops, manage resources, and tackle challenges such as plant diseases and environmental stress. By enabling real-time data collection, localized decision-making, and predictive insights, AI-powered edge computing allows for precise application of fertilizers, water, and pesticides. This not only improves crop health and yields but also minimizes environmental impact, making it a key driver of sustainable farming in an era of climate change and rising global food demand. What makes these technologies so transformative is their ability to address some of agriculture's most pressing challenges. With innovations like lightweight AI models, federated learning for decentralized data processing, and blockchain for secure data sharing, precision agriculture is becoming more adaptable and collaborative. These advancements provide farmers with deeper insights into crop conditions, pest and disease management, and resource optimization, promoting both productivity and sustainability. Additionally, by reducing dependence on cloud computing, AI-driven edge systems make it easier for farmers in remote areas to adopt these technologies. However, widespread implementation still faces significant hurdles that must be overcome for their full potential to be realized.

Despite their promise, integrating AI and edge computing into agriculture comes with challenges such as hardware limitations, inconsistent data quality, and the need for technical expertise. Many edge devices struggle with limited computing power and energy efficiency, particularly in harsh agricultural environments. Furthermore, AI models must be refined to ensure accuracy and adaptability across various crops and climates, requiring ongoing research and development. Financial barriers, connectivity issues, and a lack of farmer training further complicate adoption, especially in resource-constrained regions. To successfully implement these technologies, collaboration across multiple disciplines is essential. Scientists, engineers, agronomists, policymakers, and industry leaders must work together to develop energy-efficient hardware, robust AI algorithms, and practical training programs. Support from policymakers and agricultural extension services is also crucial in ensuring that farmers—whether large-scale producers or smallholder growers—can access and benefit from these advancements.

The future of precision agriculture depends on continuous innovation and collaboration, bridging the gap between technological advancements and practical farming applications. By addressing existing limitations and expanding the capabilities of AI, edge computing, and sensor-driven solutions, the agricultural industry can take a major step toward a more sustainable and food-secure future. These technologies have the power to meet the challenges of the 21st century head-on, ensuring a balance between feeding a growing population and preserving the environment for future generations.

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AUTHOR CONTRIBUTIONS

All authors contributed equally to this research.

COMPETING OF INTEREST

No conflicts of interest have been disclosed by the authors.

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