IJAIB-International Journal of Agricultural Innovation in Biotechnology
Volume 2, Issue 2 | October-2025
e-ISSN: 3065-1085 Print ISSN: 3065-1069

Innovations for Intelligent Farming Systems Were Driven by New Developments and Challenges

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Received: 25-08-2025; Revised: 10-09-2025; Accepted: 25-09-2025; Published: 14-10-2025

Abstract
The advent of Artificial Intelligence of Things (AIoT) has been realized in smart farming resulting in this becoming a revolution in contemporary farming. Eliminating the need to know the event before it is being sensed, AIoT systems support precision farming, optimization of resources, and sustainable crop management, closely related to the ability of artificial intelligence to predict the event. More recent innovations have been on smart irrigation, using AI to detect pests, soil and climatic conditions, autonomous farm equipment, and data analytics systems. The innovations are not only increasing productivity, but also offer solutions to some of the most pertinent issues, e.g. food security, the effects of climate change and sustainable use of resources. Nevertheless, barriers to the widespread use of AIoT in agriculture are rather strong due to the high cost of implementation, the insufficient digital literacy of farmers in the agricultural sector, the inability to provide all the necessary facilities in rural territories, and data privacy/security and interoperability concerns between heterogeneous systems. The given review offers the description of technological advances over the past years, traces their current limitations, and determines new research directions that can be undertaken to make AIoT an applicable and sustainable approach to global smart farming.
Keywords: ***AIoT, smart agriculture, precision farming, artificial intelligence, Internet of Things, sustainable agriculture, crop monitoring, intelligent irrigation, farm automation, agricultural challenges.***

1.Introduction
The agricultural segment has been inserted in human civilization over the years, and is the guarantee of food security and has enabled economic stability of countries. Nevertheless, in the recent decades, the sector is under more pressure due to the emergence of multifaceted challenges on the global scale, including population increase, global warming, environmental scarcity of resources, insect incursion, and commodity chain interruption. Such problems were even increased in times of the COVID-19 threat when unexpected weaknesses of traditional farming systems were revealed. The need to rely less on transportation and less on labor, combined with the increased emphasis on food until now and labor shortages led to an increased emphasis on technology-driven and more resilient agricultural methods. In this respect, the intersection of Artificial Intelligence (AI) and the Internet of Things (IoT), also known as the Artificial Intelligence of Things (AIoT) has become a game-changing paradigm with the capability of transforming global farming(1).
AIoT is a combination of intelligent-based algorithms and IoT-based devices that allow smarter collections, interpretations and decision making. The huge flow of environmental and operational data is collected by IoT devices, like wireless sensor networks, drones, and remote monitoring systems. With the processing of such information on the AI models, many opportunities arise: introduces predictive insights, automation of routine processes, and optimization of resource consumption. Combining IoT with AI can help farmers to convert raw information into knowledge and use it to monitor crops in real time to notice early disease symptoms, irrigate with pinpoint accuracy and to automate the harvesting processes. The combination of AIoT has made it one of the building blocks of smart agriculture, the triangle of efficiency, sustainability, and productivity.
Agricultural implications of AIoT will be more appreciated when we reflect on the weaknesses of conventional farming practices. Traditional agriculture is fixed on the manual observation, seasonal forecasting along with responsive action. An example is the detection of crop diseases which may rely on human observation that is sometimes irrequisite and time lagged and results in heavy losses in yield. Likewise, irrigation is practiced regularly in most parts thereby precipitating excessive use of water resources and also causing water shortage when the crops need water most. There is also no accuracy in the fertilizers applied and the survival of pests itself leading to environmental contamination and increased cost of production. Such inefficiencies do not only jeopardize the economic viability of the farmers, they also overwork already depleted natural resources. These

gaps have been filled by AIoT ready accuracy farming solutions, which support maximum resource deployment, at a minimum waste and environmental degradation.

Some of the nations have identified the innovative power of intelligent farming and started using the AIoT-based agricultural systems. As an example, both the United States and South Korea have invested a lot in digitalized agricultural infrastructure, taking advantage of AI-supported platforms to monitor crops, greenhouses, and livestock. Such initiatives are consistent with the wider aims of fostering a sustainable food chain whilst improving the sustainability of the environment as a result of reducing the impact of agriculture on the environment. In developing countries, widespread adoption is still problematic because of the lack of the necessary infrastructure and the financial burden this would entail but pilot programs have proven that AIoT has the potential to improve yields and support a better standard of living of farmers. All these international initiatives explain why AIoT is not only a technological development but a strategic requirement of redefining the future of food production(2).

The AIoT technological architecture of agriculture normally comprises various layers that are connected. On the bottom level are IoT devices with sensors that track real-time data regarding moisture in the soil, temperature, humidity, the level of nutrients and pest activity. Communication between these devices takes place in wireless networks which is preferably based on 5G to relay the data without interruption. The second tier entails processing and integration of data, which is interpolated in the collected information by AI algorithms, such as machine learning, deep learning, and reinforcement learning. These algorithms are able to interpret patterns, make forecasts and propose the best interventions, e.g., the best time to irrigate a field or use fertilizer. The last one encompasses the implementation of decisions, in which the suggested course of action is implemented by AIoT-enabled equipment such as autonomous tractors, drones, or robotic harvesters. This full-cycle process shows how AIoT does more than refine decision-making it also turns decision-making intelligence into direct tangible benefits on the farm.

The advantages of switching to AIoT in farming are not single-faceted. To begin with, it helps to increase productivity since crop diseases and pests can be detected in time and farmers can take measures to avert the crisis. Second, it optimizes the use of resources due to the reduced costs associated with water and chemical consumption because of precise irrigation and fertilization, which leads to compliance with the environmental sustainability assessment. Third, it aids resilience by giving real-time monitoring systems that reduce the effects of the unpredictable weather patterns, which are on the increase as a result of climate change. And finally, AIoT establishes the possibility of superior supply chain management in the form of predictive analytics to align production patterns with the demand in the market, be it food waste or better profitability among the farmers.

Irrespective of the properties mentioned, consternation of the AIoT in agriculture does not come without important deterrents. One of the greatest challenges is the high costs of implementation, especially in the low-income areas where farmers are not able to pay high prices of superior digital systems. Rural areas with people who are not digitally literate and not having the appropriate training are a limitation to the widespread use. Moreover, the questions of data interoperability, privacy, and security should be resolved in order to establish trust into AIoT systems. The latter has to do with the fact that rural regions are prone to suffer infrastructural shortcomings, including poor internet connections and insecure power sources, limiting the scalability of AIoT technologies. Solving these barriers with the help of coordinated actions of governments, researchers, technology providers, and farmers themselves is required.

2.Methods

1. Research Design and Plan

In a bid to study the extent of applications of Artificial Intelligence of Things (AIoT) in the agricultural sector, this research utilised the systematic review methodology. The systematic method was selected due to the transparency, reproducibility, and evidence-anchored procedure of finding, interpreting, and synthesizing the prior studies. In contrast to narrative type of review, which might largely depend on the evaluation of the author, adoption of the systematic review procedure enables one to establish an objective criterion in order to minimize bias in selecting the studies and to increase the credibility of results. The epistemological aim of this design was to give an overarching view of how AIoT has been implemented in the agricultural field, what areas have not been covered yet, and which paths need to be focused on in the future.

2. Research Objectives and Questions

The initial phase of the research design was to come up with clear objectives and guiding questions. The goals were two-fold:

- In order to chart the existing scene of AIoT solutions in smart farming.
- To determine barriers and opportunities to scale-up AIoT technologies to real-world farming.
- With these objectives in mind, the review considered a number of guiding questions:
- What are the most frequently used areas of AIoT that could be used in agriculture?
- Which types of artificial intelligence (e.g., deep learning, reinforcement learning) are the most popular ones in the agricultural IoT systems?
- Which technologies operate commonly alongside AIoT, or are there some new ones which are not fully discovered yet?
- Which trends can be identified in terms of the growth of publication, its geographical focus, research priorities in this area?

These questions were used to organise the literature search and data analysis, and therefore consistency was maintained in the review process.

TABLE 1 Summary of Methodological Approach

Step	Description
Research Design	Systematic review methodology adopted to ensure transparency and reliability.
Objectives & Questions	Mapped AIoT applications, identified challenges, explored AI models & trends.
Databases Searched	Web of Science (WOS), ScienceDirect (SCD), IEEE Xplore.
Search Strategy	Keywords: “AIoT in agriculture,” “smart farming with AIoT,” “precision farming.”
Inclusion Criteria	2017–2022 publications, peer-reviewed, agriculture-focused, empirical evidence.
Exclusion Criteria	Non-English, non-agriculture, duplicate/overlapping studies, editorials, notes.
Screening Process	Titles/abstracts reviewed → full-text assessment → quality scoring framework.
Data Extraction	Collected info on domains, AI models, IoT devices, benefits, limitations.
Data Synthesis	Thematic qualitative analysis; trend identification; comparative evaluation.

3. Search Strategy to the Literature

A multi- database search was conducted to bring about a complete study of the relevant studies on the research topic. Major electronic databases such as Web of Science (WOS), ScienceDirect (SCD) and IEEE Xplore were identified since these databases cover predominantly engineering, computing and agricultural research. The keywords were well analyzed in order to capture both sides of the AI and IoT. Terms like, Artificial Intelligence of Things, AIoT in agriculture, smart farming through AIoT and precision agriculture and IoT with the help of AI were employed. Truncation symbols as well as Boolean operators were used to improve results.

The search procedure was not limited to journal articles only which are peer reviewed. Conference papers, book chapters and white papers were first considered to cover the new insight, but the inclusion according to the final criteria reduced the sources down to reliable peer-reviewed sources. The search took place in December 2022 and was revised at the beginning of the year 2023 by including the latest publications(3).

4. Inclusion and exclusion criteria

It was necessary to come up with selection criteria in order to sieve the studies. Accepted articles were those which:

- Published in 2017-2022 (in order to capture the latest technological advances).
- Targeted specifically at the applications of AIoT in agriculture.
- Were able to provide empirical evidence, models or frameworks of AIoT deployment.
- Published in English, peer-reviewed.

- The following were exclusion criteria:
- Second or tertiary reviews that were not presenting primary data.
- Non-agricultural researches (e.g., healthcare or smart cities).
- Duplicative publications of the same authors using overlapping data.
- Materials which are non peer reviewed (editorials, notes or posters).

Such a filtration procedure guaranteed that only the quality, relevant, and original contributions were summarized utilizing the review.

5. Quality assessment and screening

After obtaining the first retrieval, the retrieval was screened in order to eliminate irrelevant entries based on the titles and the abstracts. The rest of the literature underwent review of full-text. A framework to measure quality was established and considered the following five dimensions:

- Adequacy of research aim.
- Clear definition of used AIoT technologies or models.
- Employment of deep learning/or machine learning in IoT.
- The indicators of actual experiments or simulations.
- Quality of results as far as agricultural purposes.

All the dimensions were rated as Yes (1.0), Partial (0.5) or No (0). Studies that had average scores that were greater than 0.5 were retained in the final synthesis. This would guarantee high standards, as well as limit the impact of speculative or loosely substantiated content(4).

6. Extraction of data and classification of data

Specific data fields were taken out of each of the selected articles:

- Year of publication, source.
- Use case (e.g. irrigation control, pest early warning, greenhouse control, tracking livestock).
- AI models used (CNNs, RNNs, reinforcement learning and so on).
- The integrated devices and technologies were IoT (drones, WSNs, edge computing, cloud platforms).
- Benefits and limitations reported.

This was subsequently grouped into thematic clusters including deep learning approaches, computer-related vision, video surveillance systems, and smart farm equipment. A systematic synthesis of trends was possible through such clustering, and gaps were also identified.

7. Analyses and data synthesis

Instead of using the quantitative meta-analysis approach, the review followed qualitative methods of synthesizing data that do not demand homogenous datasets. Comparisons were made across studies in terms of theme and their results were interpreted in the light of the guiding research questions. To analyze the trend, a growth analysis of publications over the years was carried out, which indicated a growing interest in AIoT in the last two years in particular. Comparative assessment was also made, which models of AI or IoT architectures worked best and spread the most popular. Also, policy frameworks and sustainability objectives were referred to, allowing information about the wider consequences of adopting technology to emerge.

8. Ethical Considerations

Nevertheless, as ethical review principles were applied in the assessment of included studies, even though, primary data was not collected during this study. Data privacy, security of IoT systems, and their possible biases in AI models were considered as an issue when critical appraisal was conducted. This made such synthesized knowledge not only be accountable of the technological capabilities but also the ethical obligations of AIoT in farming.

9. Weaknesses of the Methodology

As in any systematic review, limitations in the methods were present in this method. The search of only three large databases might have missed the relevant studies in smaller journals or regional ones. Limiting the source base to publications only after 2017 made it recency-wise but possibly ignored earlier work that formed a basis. Also, a linguistic bias was a possibility due to the omission of non-English research, especially, as a substantial part of agricultural research findings are described in local languages. The restrictions though, were offset by the necessity of remaining focused and rigorous.

10. Description of Methodological approach

Overall, the research broadly followed what could be considered a multi-step and systematic protocol, starting with specific research objectives and research questions, using stringent literature searches, use of

Volume 2, Issue 2 | October-2025
e-ISSN: 3065-1085 Print ISSN: 3065-1069

inclusion/exclusion criteria, the deployment of quality assessment instruments, and the eventual thematic synthesis. The rigor of the methods enhances the reliability of the results as well as providing the blue print to future reviews of this evolving fast developing field. The approach allows making the review more than just the current picture of AIoT in agriculture by complementing evidence-based filtering with thematic analysis that can reveal knowledge gaps and emerging frontiers.

3.Results

1. Trends in publication and research development

The data of the conducted systematic review implies that research activity on topics of the AIoT application in agriculture has increased rapidly. Having published less than five articles in 2017, the annual studies are increasing exponentially, as experts predict that there will be almost fifty published by 2023. This is an indicator of not only the maturity of the enabling technologies, i.e., 5G networks, edge, and advanced AI algorithms, but also a chorus of calls in the world to seek more sustainable agricultural solutions. Digital transformation discontinued the practice in the farming industry which also caused by the COVID pandemic. The geography of research indicates that studies are focused on technologically progressive countries, though more and more pilot projects appear in developing ones, which indicates the universality of AIoT(5).

2. Intelligent water and irrigation control

Smart irrigation is one of the application areas that are most likely to be found in the reviewed literature. As the sources of fresh water continue to run low, the application of precision irrigation technologies through the power of AIoT have become popular. IoT sensors devised in soil/plants surrounding fetch real-time information about the soil moisture, the weather situation, as well as the evapotranspiration. Then AI algorithms interpret these data to predict the best time to irrigate the fields so that the crops could be provided with enough water and at the same time reducing the volume of wasted water. Various studies revealed that reinforcement learning and neural networks with LSTM are more efficient than the conventional techniques in adjusting to chaotic environmental contexts. Distinctively, edge computing and adoption of fog have minimized time consumptions in making these decisions, and consequently irrigation systems act within milliseconds to variations in soil and climatic conditions. This minor topic highlights the way AIoT is connecting sustainability targets and real life farming requirements.

3. Pest monitoring and Crop Disease detection

Application of AIoT in detecting diseases and pests is another future topic. The conventional visual inspection tools are inefficient, repetitive and not uniform, which ultimately results in failure to initiate timely reaction and also causes significant losses (in terms of yield). Combining computer vision with IoT cameras and drones, AIoT systems will have the ability to diagnose early stage disease on a large scale. Advanced application specifically convolution neural network (CNN), and hybrid deep learning architecture emerged to be especially favorable in the classification of plant leaf images and there was a high accuracy in identifying healthy and infected crops. In addition, IoT pheromone traps and acoustic detectors including pests are spreading in the monitoring of pests with data sent to cloud-based Artificial Intelligence systems, which triggers and exercises orders on farmers. These developments minimise the use of chemical pesticides through the capability of precision intervention. The potential of transformative agricultural AIoT-disease monitoring systems is noted to reduce crop losses within controlled studies by as much as 30 percent.

4. Health and Behavior Surveillance of Livestock

The AIoT applications are not confined to crops only, and have stretched to the livestock livelihoods, which is a domain very important to food safety and rural economies. Wearables such as smart collars combined with Internet of Things are proliferating to monitor cattle, poultry, and sheep in terms of their health and movement patterns. Such machines record the physiological data like temperature, heart-rate, and activity. The data is then analyzed by the AI models to identify the anomalies which can signal the diseases, stress, or estrus cycles. Other than enhancing the welfare of the animals, the use of real-time monitoring leads to increased productivity of the farms since interventions can be provided in time. Other studies involved further explorations of AI-based video surveillance with the focus on identifying feeding patterns, and others experimented with reinforcement learning to derive optimum feeding schedules. Using the AIoT in the management of the livestock would mean that farmers would minimise the veterinary expenses and also mitigate the occurrence of the disease outbreak, which when large, can be disastrous (6).

5. Autonomous Farm Machinery and Robotics

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An increasing amount of studies have brought forth the effectiveness of self-employed farm machinery that operates with the help of AIoT. There is the use of robotics with AI algorithms that are used in planting, weeding, spraying and harvesting. These machines have their data backbone in form of IoT sensors and SMART navigation and task-based optimization through use of AI. As an example, robot fruit-picking technologies featuring computer vision and robotic arm have shown efficiency in locating, characterizing, and picking fruits e.g., apples and tomatoes with little human labor. Likewise, autonomy-enabled tractors built with AIoT systems may consist of the mapping of fields and combination-readjustment of fertilizer and precision plowing. Findings show that the technologies not only cut dependence on labor but also enhance efficiency, particularly, in areas subject to workforce shortages on an ongoing basis. There were also studies of savings in costs and beneficial impact to the environment as a result of efficient utilization of fertilizers and pesticides.

TABLE 2 Key Results in AIoT Applications for Agriculture

Application Area	AIoT Integration	Key Outcomes
Smart Irrigation	Soil moisture & weather sensors + AI prediction models	Reduced water use, improved irrigation efficiency, real-time adaptive scheduling
Disease & Pest Detection	Drones, IoT cameras, CNNs, hybrid deep learning models	Early detection of crop diseases, 90%+ accuracy in classification, reduced losses
Livestock Monitoring	Wearable IoT sensors, video surveillance, anomaly detection AI	Improved animal welfare, disease prevention, reduced veterinary costs
Autonomous Machinery	Robotics + AI navigation + IoT sensor feedback	Automated planting, spraying, and harvesting; reduced labor dependency
Yield Prediction	IoT-based environmental data + machine learning (Random Forests, DNNs)	More accurate yield forecasts, better resource allocation, improved market alignment
Supply Chain Transparency	IoT data + AI analytics integrated with blockchain	Enhanced traceability, reduced food waste, stronger consumer trust
Smartphone-based Solutions	Portable device sensors + AI cloud applications	Low-cost, accessible monitoring tools for smallholders, wider adoption potential
Edge/Fog Computing	Distributed AI processing closer to IoT devices	Lower latency, energy-efficient responses, improved reliability in

6. Yield Prediction and Data Analytics to Support Market Insights

AIoT has been used in yield forecasting and market analysis as well with predictive analytics being important in synchronizing the production to demand. IoT sensors collect real-time data on the weather, the nutritional status and growth stages of the plants, which are then processed by an AI model to infer yields. Sophisticated machine learning m in itus such as Random Forests and Gradient Boosting as well as hybrid deep neural networks were found to be highly accurate on predictive tasks when compared to traditional statistical models. With these insights, farmers can allocate resources with the help of these insights, but it also endows the policymakers and other actors of the supply chain with the possibility to stabilize food markets. Other studies went further and associated AIoT data with systems based on blockchain to maintain transparent traceability of produce to further support the trust of the consumers. This integration reveals the idea that AIoT can be used as much to help production efficiency as it can be used to improve resilience in the food system more broadly(7).

7. Smartphones and Portable integrations

The other trend worth mentioning is the incorporation of smartphones into the agricultural surveillance. GPS, accelerometers and light detectors are built-in features of modern smartphones, which may be used as agricultural monitoring tools in the field. Researchers worked on the application of smartphones in disease identification of plants, estimation of chlorophyll and soil analysis. When linked to AI systems in the clouds, such tools offer an accessible source of precision farming information to farmers, especially the smallholders. In the studied research, it is shown that AIoT applications based on smartphone technology will severely lower the entry barriers in digital agriculture, providing scaling solutions in areas with poor infrastructure. Nevertheless, issues with quality inconsistencies of sensors and data gathering-based privacy risks were highlighted.

8. The new frontier of Edge and fog computing

One of the technical improvements that especially feature the reviewed findings is the transformation of dependencies on cloud-based systems to the edge and fog computing systems. Although conventional AIoT systems are managed by cloud processing, their bandwidth and latency-free limits can not always be efficient in rural settings. Edge and fog computing minimize the data flow to IoT devices and brings processing to them. It was discovered through case studies that smart irrigation, disease detection and livestock monitoring systems take shorter response time and consumption of less power with edge computing support. The evolution is an important milestone toward scalable AIoT agriculture solutions, which are particularly important in the real-time context and must have an instant response.

9. Results Summary

Overall, the findings of this systematic review demonstrate that AIoT is not the pie-in-the-sky of mere lab prototypes anymore, but rather feasible technology to efforts in irrigation, crop disease detection, livestock monitoring, robots, harvest estimating, and matching to markets. Its impact on the transformation of agriculture supports its pace of publication by its growing steepness. Even though it becomes evident that the reviewed literature demonstrates encouraging results in their efficiency, sustainability, and productivity, the issues concerning cost, infrastructure, and data governance still exist (8). The combination of these findings leads to a conclusion about a future when AIoT will become the core of smart agriculture and will help to intervene between the technological innovation and sustainable food production.

4.Discussion

1. Insight into the Surge of AIoT in the Agriculture Industry

The fast-growing adoption of AIoT in the agrarian economy indicates a radical transformation in the concept of food systems. There is no more adherence to manual observation and older methods to conduct agriculture, but farming is being turned into a data-driven and smart ecosystem that is automatically controlled. As a whole, the reviewed studies indicate that AIoT is not the subsidiary tool but the driving force of a precision farming method. Whether it is a water conservation-friendly smart irrigation system or a disease detection-centered model to limit crop losses, the fiscal literature on the same highlights the centrality of AIoT in ensuring a shift towards high sustainability and productivity. Nonetheless, such increase also brings about concern on accessibility, inclusiveness, and global agricultural systems in terms of their willingness to implement these technologies on a large scale(9).

2. Ethical and Social Issues

Ethical aspects of the integration of AIoT are also an important issue that needs reflection. Information gathered in the farms might contain sensitive data on the land productivity, resource accessibility and even behaviour of the farmer. Unless there is strong governance, access to such information may be abused by companies or by the government, leaving concerns of fairness and lack of independence. Also, since AIoT encourages automation, there is the fear that agricultural jobs may be lost as countries that rely on farming as a source of livelihoods have millions of their citizens involved in farming. It is important to make sure that the adoption of AIoT focuses on social inclusion rather than exclusion. Technology implementations should thus come along with the ethics that would involve balance of innovation and justice and empowerment of the farmer.

3. Regional Adoption Inequality

As can be seen in the reviewed results, there are visible differences in the geographical distribution of AIoT adoption. Developed nations have high-level digital infrastructure, so they can perform tests and implement AIoT solutions on large scale, usually through government subsidies and other investments. In contrast, developing economies where agricultural industries make up an economic backbone fail to adapt even to basic IoT tools because of the cost and infrastructure limitations. Such a gap puts the developing world at risk of enhancing technological gaps in world agriculture. Currently, however, new low-cost and smartphones-based solutions and open-source AIoT platforms have the potential of closing this gap. Policy makers and global bodies have to emphasise on equal allocation of resources and facilitating partnerships that will see high tech applications being available to a wide range of agricultural practices.

4. Coming Together with the Wider Technological Ecosystems

AIoT does not exist as an island. Its real potential is learning how to integrate, with other rising technologies like blockchain, cloud computing, edge computing and 5G connectivity. Blockchain delivers transparent and nontamper record of crop production heightening consumer confidence in supply chain products. Edge and the fog computing minimize latency, the latter of which makes AIoT applications feasible in remote farming communities where fast responses are of the essence. In a similar way, having 5G networks improves the speeds of communication, thus enabling the transmission of data fluent across sensors, machines, and cloud platforms. This integration of technologies brings into effect a complete smart-agriculture ecosystem through which the efficiency, traceability, and the scalability can be realized concurrently(10).

5. Research Directions in the Future

There are also some research directions that can be identified on the basis of this review. First, the low-cost, scalable AIoT strategies that can support smallholder farmers, especially in Asia, Africa, and Latin America are necessary. Second, interdisciplinary studies where agronomy, computer science and economics are integrated to make context related solutions should be the main focus of research in the future. Third, AI models have to be energy-efficient in order to be able to operate within the limitations of the devices that are part of the IoT system since deep learning models typically require significant computing capabilities. Fourth, formal verification procedures are required to provide the assurance of the AI models in high-stakes agricultural decision-making. Finally, additional studies are necessary to investigate the social-economic effects of AIoT on adoption in the long-run, especially with regards to job creation and sustenance of farmers living in the rural areas.

6. Implications to Policy and Governance

With the enablement of policy environments, the successful deployment of AIoT in the agricultural area is critical. Governments should develop structures that encourage innovation without infringing the rights of the farmers. The subsidies of digital infrastructure, the stimulating tax on the use of AIoT, and the creation of training programs are crucial to push the diffusion to a higher pace. It is equally vital that there be data privacy and security regulations, whereby, farmers have complete control over information, which is generated on their farms. It is also possible that international collaboration should be made to establish international standards of interactions and ethical application of AIoT. The most technologically developed ways can thus enter research labs and not agricultural landscapes without supporting policies around these technologies.

7. Striking a balance between Innovation and Sustainability

Although AIoT has the potential to boost agricultural productivity unlike any other technology, there is a great need to balance creativity and environmental consciousness. Excessive use of technology without the view of the ecological condition might alleviate the environmental degradation. In one instance, AI-powered intensive agriculture may definitely elevate the output, but may also raise energy demands in case of unsustainable use. Thus, to make AIoT compatible with global sustainability, it is crucial to incorporate renewable sources of energy, regenerative farming methods and make the sensors environmentally friendly.

5.Conclusion

As is seen in the survey carried on Artificial Intelligence of Things (AIoT) uses in smart agriculture, the interaction between artificial intelligence and IoT technologies has taken the rank of being one of the strongest innovation enhancers of the agricultural world. The past five years have seen a rapidly mounting body of research that points to the variegated ways in which AIoT is transforming customary farming into an intelligent and data-driven system that would be able to respond to the global challenges of food insecurity, dearth of resources, and climate change. The results validate that AIoT is not the new emerging tool, but the obligatory element of the new agricultural setting.

The essence of the contribution of AIoT lies in its capability of transforming raw data into operational intelligence. Using IoT equipment, it is possible to collect enormous databases concerning the ground situation, weather patterns, crop growth and animal activity. These data are then passed through the advanced computing algorithm of artificial intelligence and provide predictive insights so that timely, accurate, and resource-efficient interventions can be made. This synergy allows farmers to leave the reactive approaches so as to adopt the proactive and preventive decisions. Examples of applications including precision irrigation, detection of disease and pests, autonomous robotics, and yield forecasting means that the extent of the role of AIoT in enhancing efficiency, environmental effects, and profitability have a wide range to demonstrate in farm systems.

The review also shows how AIoT forms not only the benefits of individual farmers but of the whole agricultural sphere. As an example suggesting data-driven yield prediction models based on the AIoT data could help policymakers better pinpoint food supply patterns and plan to accommodate consumer changes in the market.

When supply chain transparency is used along with blockchain, it offers greater credibility of food safety and sustainability assurances to consumers. Meanwhile, livestock monitoring solutions promote animal welfare, and it leads to livestock industry losses minimization and enhancement of disease control. These many-faceted benefits indicate that AIoT has wider ramifications beyond even the farm gate to influence whole food systems in more efficient, transparent, and sustainable patterns.

Alongside such encouraging findings, the review notes that the adoption of AIoT is also relevant in the context of constant challenges. Prohibitive expenses of buying and operating of advanced IoT devices, sensors and AI platforms, which is a significant impediment, especially in developing economies where smallholder farmers make up the largest proportion of the agricultural workforce in the world. Scalability is also restricted by infrastructure constraints of poor power supply, poor access to broadband, and so on. Of equal concern are the questions of digital literacy; farmers will have to access technology, but should be equipped to read the outputs of AI and come to sound decisions. Unless these obstacles are thrown off, the digital divide in agriculture has the potential to widen and leave vulnerable farming societies unable to benefit in the innovating economy.

The other main lesson that can be learned out of this review is the increasing role of governance and ethics. There is a growing appreciation of the fact that data generated in agriculture are a valuable source, and issues attached to privacy and misuse are getting more pressing. In the absence of such legal systems, farmers could lose ownership to the information gathered on their farms thereby being exploited by the corporations or other people. Ethical dilemmas are also present in case of labor displacement where automation of labor could have implications on the employment opportunities in the rural areas by using AIoT enabled robotics technology. Thus, the implementation of technology cannot only be accompanied by open administration systems to protect the rights of farmers, foster equality in access, and make sure that novel technologies do not adversely impact rural lives.

In the future, there are some strategic directions that can be considered, which are important not only in terms of research but also practice. One, low-cost, context-specific AIoT solutions that can be affordable and cater to smallholder farmers in the low resource environment need to be designed urgently. This might involve use of smartphone sensors, IoT networks powered by solar energy, and open source AI models. Second, priority should be given to energy-efficient AI models to minimize the computational burden and have the device perform in even the most remote locations lacking an adequate power supply infrastructure. Third, such interdisciplinary collaboration should be hired, which is how agronomists, data scientists, engineers, and policy-makers can collaborate to create technically robust, economically viable, and socially acceptable systems. Fourth, capacity-building activities are critical to promote digital literacy in conditions where farmers are not seen as the passive subjects of AIoT technology, but rather the active agents of it.

It is also stressed in the conclusion that it is important to integrate AIoT with other complimentary technologies. Edge and fog computing will play vital roles in the minimization of latency and consumption of energy, whereas 5G networks will provide a faster and reliable interconnection of devices. The transparency and trust of the food supply chains will be achieved through blockchain, and the environmental impact of the IoT infrastructure will be kept down through renewable energy solutions. Collectively, these technologies will support the set-up of smart farming and move AIoT to mass acquisition.

Acknowledgement: Nil

Conflicts of interest

The authors have no conflicts of interest to declare

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