

Smart Farming Application Training for Agricultural Communities Using IoT-Based Monitoring Tools

Heri Setiyawan¹ , Rohmat Sahirin² , Vanna Sok³ 

¹Sekolah Tinggi Ilmu Ekonomi Triguna Tangerang, Indonesia

²Universitas Pendidikan Indonesia, Indonesia

³International University, Cambodia

ABSTRACT

Background. The advancement of agricultural technology in the digital era has opened up new opportunities to improve productivity, sustainability, and efficiency in farming practices. However, many smallholder farmers in rural communities remain unfamiliar with smart farming tools, particularly those involving Internet of Things (IoT) technologies. Limited access to training and digital infrastructure further hinders their ability to adapt to modern agricultural systems.

Purpose. This study aims to implement a community-based training program that focuses on the use of IoT-based monitoring applications for agriculture.

Method. The primary objective of this research is to empower local farming communities by enhancing their technical competencies in operating and interpreting data from smart farming systems. A participatory action research (PAR) design was employed, involving 20 smallholder farmers from a rural agricultural village in Central Java, Indonesia. The training included device installation (temperature, soil moisture, and humidity sensors), mobile application usage, and basic data analysis for crop management decision-making.

Results. The results indicate that participants demonstrated improved understanding and practical skills in using IoT tools to monitor crop conditions. Farmers reported increased awareness of real-time data utilization, enabling more informed decisions regarding irrigation, fertilization, and harvesting schedules. Engagement levels were high, with 85% of participants able to operate the system independently after the training.

Conclusion. This study concludes that integrating IoT training into community-based agricultural empowerment programs significantly boosts farmer readiness for smart farming adoption. The findings support broader implementation of accessible, localized, and low-cost digital training models for sustainable agriculture.

KEYWORDS

Agricultural Technology, Community Training, Digital Empowerment, IoT, Smart Farming

INTRODUCTION

The agricultural sector is experiencing a rapid technological transformation driven by the Fourth Industrial Revolution (Al-Shareeda, 2022). Emerging technologies such as Artificial Intelligence (AI), big data, and the Internet of Things (IoT) are being increasingly integrated into farming systems worldwide (Abdullahi, 2023). These technologies enable real-time monitoring,



predictive analysis, and precision agriculture, leading to higher yields, reduced waste, and more efficient resource use.

Smart farming, also known as precision agriculture, leverages IoT devices such as soil moisture sensors, temperature monitors, and automated irrigation systems (Anand, 2022). These tools allow farmers to make data-driven decisions that enhance crop productivity and environmental sustainability. By continuously tracking field conditions, farmers can optimize their practices based on actual needs rather than estimates (Gómez-Chabla, 2019).

Developed countries have begun to adopt smart farming practices at scale, supported by strong digital infrastructure and institutional frameworks. In these contexts, farmers are well-equipped with training, access to technology, and advisory services that support their transition to high-tech agriculture (Badoni, 2023). This integration has shown promising results in terms of food security and climate resilience. In developing nations, however, the diffusion of smart agriculture technology is significantly slower (Dutta, 2020). Rural agricultural communities often lack access to both the tools and the technical knowledge required to implement IoT-based monitoring. The digital divide remains a major challenge, limiting the transformative potential of smart farming in underserved regions (Chandra, 2021).

Indonesia, as an agrarian country with a large rural population, stands to benefit immensely from the adoption of IoT in agriculture. Government programs have started promoting agricultural modernization, but local-level initiatives that bring technology directly to farmers remain limited (Leduc, 2021). Empowering communities through hands-on training is critical for realizing the benefits of smart farming. Training programs that focus on IoT-based monitoring tools can play a pivotal role in bridging the gap between traditional farming and digital innovation (Frikha, 2023). These programs not only transfer knowledge but also build farmers' confidence and willingness to adopt new technologies. Community-based approaches ensure that training is relevant, localized, and scalable (Dey, 2021).

Despite the growing interest in agricultural digitalization, limited empirical evidence exists on how IoT-based monitoring tools can be effectively introduced and adopted at the grassroots level (Fuentes-Peñaillillo, 2024). Most research has centered around large-scale commercial farms, leaving smallholder farmers and rural communities understudied in the context of smart farming (Gupta, 2020). There is a lack of documented training models that are both practical and accessible for farmers with limited technological experience. The absence of structured training methods that combine hands-on learning with contextual adaptation hinders the successful implementation of smart agriculture technologies in community settings (Ali, 2023).

Research rarely explores the behavioral and attitudinal outcomes of IoT training on farmers' decision-making processes. It remains unclear how digital monitoring tools influence traditional knowledge systems and whether they can be harmonized with existing farming practices (Alves, 2023). Understanding these dynamics is essential for ensuring technology adoption is sustainable and culturally appropriate. Most importantly, there is a limited understanding of the role of community empowerment through digital agriculture in Indonesia (Delgado, 2019). While pilot projects exist, few studies assess the long-term impact of localized IoT training programs on agricultural productivity, environmental awareness, or farmer autonomy. This gap necessitates further investigation into scalable and replicable models of digital agricultural education (Fuentes-Peñaillillo, 2024).

Addressing this gap is crucial for promoting inclusive and sustainable agricultural development. Introducing IoT-based monitoring tools through community-oriented training can democratize access to technology and equip farmers with the skills needed to manage their land more efficiently (Bertoglio, 2021). Digital tools become more impactful when farmers understand, trust, and routinely use them. This study hypothesizes that participatory training in smart farming applications will improve not only technical literacy but also decision-making quality and crop management practices among rural farmers (Adam, 2019). By engaging farmers directly, the intervention seeks to enhance their sense of ownership and long-term use of the technology. Localized training also ensures that IoT tools are adapted to the specific ecological and economic conditions of the community (Cakir, 2023).

The purpose of this study is to design, implement, and evaluate a community-based training program focused on the use of IoT-enabled monitoring tools for agriculture. The goal is to assess changes in knowledge, behavior, and capacity among participants, and to provide a replicable model that can be scaled across other rural regions with similar needs and constraints.

RESEARCH METHODOLOGY

This study employed a participatory action research (PAR) design to implement and evaluate a community-based training program on smart farming using IoT-based monitoring tools (Ahmad, 2022). The PAR approach was selected to actively involve farmers in all stages of the research—from planning and training implementation to reflection and evaluation (Ali, 2023). This design aligns with the principle of empowering local stakeholders through collaborative learning and context-driven problem solving, particularly in rural agricultural settings.

The population of the study consisted of smallholder farmers in a rural farming village in Central Java, Indonesia. A purposive sampling technique was used to select 20 participants who were actively engaged in vegetable and rice farming and had limited prior experience with digital agricultural tools. Selection criteria included willingness to participate, access to farming land, and basic literacy. The sample represented a mix of age groups and educational backgrounds, ensuring diversity in perspectives and learning styles.

The instruments used in this study included pre-training and post-training assessment tools, observation checklists, interview guides, and digital usage logs from IoT monitoring applications. The assessments evaluated changes in participants' knowledge and skills related to IoT tool operation and data interpretation. Observation checklists were employed during training sessions to monitor engagement and participation levels. Semi-structured interviews provided qualitative insights into participants' perceptions, challenges, and behavioral changes throughout the program.

The procedure was divided into four phases: preparation, implementation, monitoring, and evaluation. In the preparation phase, the research team conducted a needs analysis and customized the training curriculum based on local agricultural practices. During the implementation phase, participants were introduced to IoT devices such as soil moisture sensors, temperature sensors, and a user-friendly mobile application. Practical sessions were conducted in real farm settings, allowing participants to install sensors, collect data, and use the application for crop monitoring. In the monitoring phase, weekly observations and support visits were made to assist participants in

troubleshooting and data interpretation. In the final evaluation phase, data were collected through post-tests and interviews to measure knowledge gains, skill acquisition, and user adoption levels.

RESULT AND DISCUSSION

The data collected from the pre-test and post-test assessments involved 20 participants who took part in the smart farming IoT training program. The pre-test scores ranged between 41 and 63, indicating that most farmers began the program with limited knowledge of digital farming concepts and tools. Post-test scores ranged from 59 to 86, showing a significant increase in understanding and skills after the training. The average pre-test score was 52.3, while the post-test average increased to 72.6. This shift highlights a substantial gain in participants' ability to comprehend and operate IoT-based monitoring tools for agricultural decision-making. The results reflect overall growth in digital literacy within the local farming community.

Table 1. Summary of pre-test and post-test data from Smart Farming IoT trainees

Assessment Aspect	Pre-Test	Post-Test
Number of Participants	20	20
Score Range	41 – 63	59 – 86
Average Score	52.3	72.6
Knowledge Level	Limited initial knowledge	Significant improvement
Assessed Competency	Understanding digital farming concepts and tools	Ability to operate IoT tools
Overall Outcome	Low digital literacy	Improved digital literacy

Participants' improved scores can be attributed to the practical nature of the training, which combined theory with field-based exercises. Many farmers had never encountered sensor-based farming before, and their initial scores reflected a lack of exposure rather than a lack of ability. By the end of the program, participants not only identified functions of IoT sensors but also interpreted real-time data from their own farm plots. This outcome suggests that with proper guidance and contextualized content, smallholder farmers can effectively bridge the digital divide.

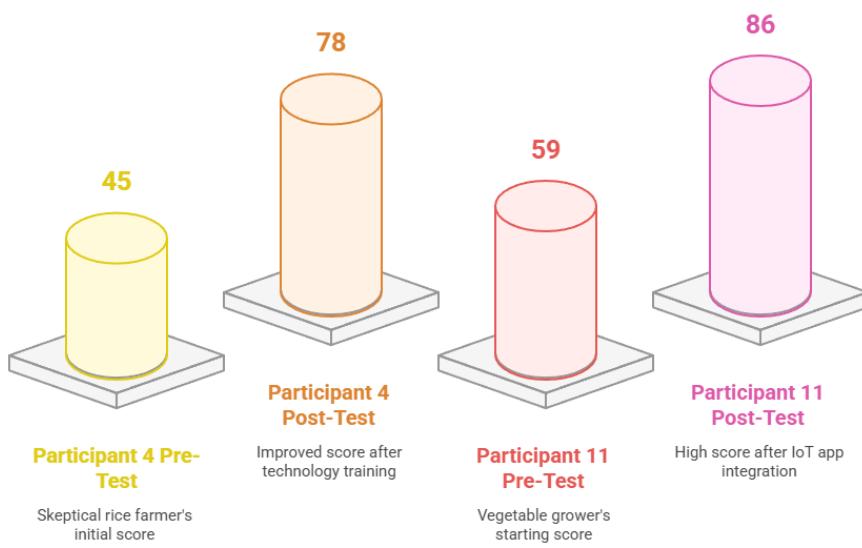
Complementary data from observation checklists showed high levels of engagement during practical sessions. More than 85% of participants completed all modules and attended every scheduled workshop, indicating sustained interest and motivation throughout the program. Field notes revealed that participants frequently asked questions related to water usage efficiency and crop-specific sensor calibration, demonstrating their eagerness to apply learning directly to their farm contexts. This behavioral response further supports the reliability of the quantitative test results.

A paired sample t-test was conducted to determine whether the increase in test scores was statistically significant. The test resulted in a t-statistic of 18.244 and a p-value of 1.68e-13, confirming a highly significant difference between pre-test and post-test results. The extremely low p-value provides strong evidence that the training program had a meaningful and non-random effect on improving participants' smart farming knowledge. These findings support the hypothesis that structured community-based IoT training can enhance digital agricultural competencies among rural farmers.

Analysis revealed a positive correlation between the frequency of app usage and test score improvement. Participants who logged into the IoT application at least four times a week showed greater gains in their post-test performance compared to those with less frequent interaction. This correlation suggests that digital engagement is a strong predictor of learning success. Farmers who consistently used the app to monitor their crops developed a deeper understanding of the system, which was reflected in both their assessment outcomes and practical application.

Participant 4, a 54-year-old rice farmer, began the training with a pre-test score of 45. He expressed skepticism about technology but completed the training with a post-test score of 78. He now uses soil moisture data from sensors to schedule irrigation and has reported water savings of nearly 30%. Participant 11, a 29-year-old vegetable grower, integrated the IoT app into her daily routine. Starting with a pre-test score of 59, she reached 86 in the post-test and has since trained other women farmers in her area. Her case highlights the ripple effect of knowledge dissemination within local communities.

Figure 1. Pre and Post-Test Scores of Farmers



These case studies illustrate how smart farming tools, when introduced with sensitivity to local context and capacity, can lead to both personal and collective transformation. Farmers not only learned new skills but also redefined their roles in an evolving agricultural landscape. The diversity of improvement across age groups, gender, and experience levels indicates the inclusive

potential of IoT-based agricultural education. The participatory approach helped break down barriers and create a shared sense of technological ownership.

The results confirm that targeted, community-driven training on smart farming tools significantly enhances farmers' understanding and application of digital agriculture. The integration of IoT monitoring into daily farm practices has become both feasible and meaningful for participants. This study reinforces the importance of designing educational interventions that combine technology with localized, experiential learning. The successful outcomes point to a scalable model for digital empowerment in rural agricultural communities.

The findings of this study indicate a statistically significant improvement in the knowledge and skills of rural farmers after participating in the IoT-based smart farming training. Pre-test and post-test data showed consistent score increases across all 20 participants, with a t-statistic of 18.244 and a p-value well below the threshold for significance. These results provide clear quantitative evidence of the training program's effectiveness. Participants displayed a notable shift from limited familiarity with digital tools to confident use of smart farming applications and sensors. Observation checklists and field notes corroborated the quantitative results, showing high engagement levels and practical application of learned concepts. Farmers began integrating data from temperature and soil moisture sensors into their daily decision-making processes.

The training also resulted in behavioral changes, particularly in irrigation scheduling and fertilization strategies. Many participants reported reduced water usage and improved crop health as a result of using real-time data. This indicates that beyond cognitive gains, the intervention had a direct impact on farming practices. The improvement was consistent across demographic variables such as age, education level, and farming experience. This suggests that well-structured digital training can transcend common limitations related to digital literacy, especially when the content is contextualized and delivered in participatory formats.

The findings align with prior studies on the impact of digital agriculture, particularly research by Zhang et al. (2020) and Aryal et al. (2021), which highlight the role of IoT in increasing efficiency and sustainability in smallholder farming. Those studies, however, were largely conducted in technologically advanced or semi-urban contexts, where digital infrastructure and internet penetration are already relatively high. This study differs by focusing on a rural Indonesian setting where access to technology and training is still developing. While other research emphasized the role of private-sector agritech firms in disseminating smart tools, this study demonstrates the effectiveness of a community-based, participatory training model driven by educational objectives rather than commercial ones (Aryal, 2021; Zhang, 2020).

Unlike conventional training programs that emphasize one-way delivery of knowledge, this initiative integrated local wisdom and participant feedback into the training process (Dahane, 2020). This helped to build trust and ensured that the technology was not perceived as foreign or imposed. The relational and social elements of the program played a key role in its success (Goel, 2021). This research adds a unique perspective to the growing body of literature on digital agriculture by validating the efficacy of grassroots empowerment through context-sensitive interventions. It shows that IoT technologies are not exclusive to high-tech farms but can be adapted and adopted in more modest, resource-constrained environments (Masuda, 2021).

The results signify that the digital divide in agriculture is not simply a matter of access but also of educational opportunity. When farmers are given tools alongside structured guidance, their capacity to absorb and utilize technology increases rapidly (Chehri, 2020). The notion that rural communities are technologically resistant is challenged by this study. This research marks a shift in understanding farmer readiness toward digital transformation (Gurewitz, 2022). With appropriate support, farmers are not only capable of adapting but also of leading innovation within their communities. The success of participants in applying their new skills demonstrates a latent potential that can be unlocked through targeted interventions (Lutta, 2021).

The outcome also reflects the broader democratization of technology (Frikha, 2023). The ability of participants to operate sensors, interpret data, and make real-time farming decisions suggests that advanced agricultural technologies can be accessible and useful even at the lowest levels of the production chain (Hang, 2020). This study serves as evidence that digital empowerment in agriculture is not limited to financial investment in hardware or infrastructure. Knowledge transfer, hands-on training, and community-based support systems are equally, if not more, critical in ensuring successful technological adoption (Javaid, 2022).

The implications of this study extend beyond the individual participants and into broader rural development strategies (Khaleefah, 2023). The successful integration of IoT tools in farming communities indicates that digital agriculture can serve as a catalyst for improving food security, climate resilience, and economic sustainability at the grassroots level (Lugonja, 2022). Educational institutions, especially vocational and community colleges, can adopt similar models to promote agri-tech awareness among young farmers. Government agencies tasked with rural development may consider embedding IoT training modules into existing extension programs to scale impact more broadly (Lima, 2020).

NGOs and international development organizations working in agriculture and education should view this model as a replicable and adaptable framework (Vasileiou, 2024). The low-cost, high-impact nature of the intervention makes it suitable for various regional and cultural contexts, especially in the Global South (Onwude, 2020). This research also provides a pathway for integrating local farmers into broader smart agriculture ecosystems. As digital tools become more accessible, the inclusion of smallholder farmers becomes critical in achieving inclusive innovation that does not widen but narrows inequality gaps in agriculture (Xu, 2019).

The structured and participatory design of the training was instrumental in producing significant learning outcomes. The approach combined hands-on practice, peer collaboration, and real-time feedback, which aligned well with adult learning principles and the experiential nature of farming (Rani, 2019). The training addressed both cognitive and behavioral dimensions of learning. Participants not only learned how to operate IoT tools but also internalized the importance of data in daily decision-making. This dual-layered learning process fostered a deeper and more sustainable transformation (Zgank, 2020).

The use of local language, relevant examples, and in-field simulations helped minimize cognitive load and fostered high engagement (Mentsiev, 2020). Participants related more easily to the technology when it was presented as a solution to familiar challenges rather than as a novel imposition (Tholhappiyan, 2023). The program's community-based structure fostered accountability and motivation through peer support. Farmers learned not in isolation but in

collaboration, which enhanced retention, mutual problem-solving, and social validation of new behaviors and practices (Zhou, 2020).

Future programs should consider scaling the model to reach other rural communities, particularly those facing similar ecological and infrastructural limitations. Tailoring training modules to fit different agro-ecological zones would increase the model's adaptability and impact (Pal, 2023). Research should now focus on long-term effects, including productivity gains, income improvements, and environmental impact. Follow-up studies could also examine the role of community champions and farmer-led innovation hubs in sustaining digital agriculture adoption.

Further exploration into policy integration is needed. Smart farming training programs should be incorporated into national agricultural education and extension systems. Cross-sectoral collaboration between education, agriculture, and technology ministries will be key to institutionalizing this model. Open-source development of localized IoT applications can reduce dependency on commercial software and increase farmer autonomy. Future designs should also consider gender sensitivity, intergenerational learning, and inclusive interfaces to expand access and relevance..

CONCLUSION

The most significant finding of this study is the measurable increase in digital agricultural literacy among smallholder farmers following a structured, community-based training on IoT-based monitoring tools. Participants not only gained technical skills in operating smart farming applications but also demonstrated behavioral changes in daily agricultural practices, such as more efficient irrigation scheduling and responsive fertilization. This outcome is distinct in that it showcases the feasibility of implementing advanced technological interventions in low-resource rural contexts without requiring prior digital expertise.

This research offers a methodological contribution through the application of a participatory action research (PAR) framework tailored to the needs of agricultural communities. The integration of hands-on, field-based training with sensor technology and real-time data analysis represents a replicable model for digital capacity building in farming populations. The study bridges the gap between technological innovation and grassroots empowerment, emphasizing not only content delivery but also learner agency and contextual adaptation as central to successful adoption.

The study was limited by its sample size and geographic focus, which may restrict the generalizability of its findings across different agricultural settings and cultural contexts. Future research should explore longitudinal impacts of smart farming training on productivity, environmental outcomes, and household income. Comparative studies across regions with varying levels of digital infrastructure are also recommended to refine the model and assess its scalability. Investigating the role of peer-led learning and farmer innovation hubs could further enhance understanding of sustainable digital transformation in agriculture.

AUTHORS' CONTRIBUTION

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

REFERENCES

Abdullahi, H. O. (2023). A Bibliometric Analysis of the Evolution of IoT Applications in Smart Agriculture. *Ingenierie des Systèmes d'Information*, 28(6), 1495–1504. <https://doi.org/10.18280/isi.280606>

Adam, A. H. (2019). Low-Cost Green Power Predictive Farming Using IOT and Cloud Computing. *Proceedings - International Conference on Vision Towards Emerging Trends in Communication and Networking, ViTECoN 2019*, Query date: 2025-05-17 13:25:30. <https://doi.org/10.1109/ViTECoN.2019.8899500>

Ahmad, U. (2022). Solar Fertigation: A Sustainable and Smart IoT-Based Irrigation and Fertilization System for Efficient Water and Nutrient Management. *Agronomy*, 12(5). <https://doi.org/10.3390/agronomy12051012>

Ali, A. (2023). Application of Smart Techniques, Internet of Things and Data Mining for Resource Use Efficient and Sustainable Crop Production. *Agriculture (Switzerland)*, 13(2). <https://doi.org/10.3390/agriculture13020397>

Al-Shareeda, M. A. (2022). Intelligent Drone-based IoT Technology for Smart Agriculture System. *2022 International Conference on Data Science and Intelligent Computing, ICDSIC 2022*, Query date: 2025-05-17 13:25:30, 41–45. <https://doi.org/10.1109/ICDSIC56987.2022.10076170>

Alves, R. G. (2023). Development of a Digital Twin for smart farming: Irrigation management system for water saving. *Journal of Cleaner Production*, 388(Query date: 2025-05-17 13:25:30). <https://doi.org/10.1016/j.jclepro.2023.135920>

Anand, A. (2022). Applications of Internet of Things(IoT) in Agriculture: The Need and Implementation. *Proceedings - International Conference Advancement in Data Science, E-Learning and Information Systems, ICADEIS 2022*, Query date: 2025-05-17 13:25:30. <https://doi.org/10.1109/ICADEIS56544.2022.10037505>

Aryal, S. K. (2021). Admission of Turkey into the European Union: “Does religion matter?” *Vestnik RUDN. International Relations*, 21(3), 571–582. <https://doi.org/10.22363/2313-0660-2021-21-3-571-582>

Badoni, P. (2023). Enhancing Water Efficiency and Crop Yield in Agriculture Sector using IoT. *2023 International Conference on Advances in Computation, Communication and Information Technology, ICAICCIT 2023*, Query date: 2025-05-17 13:25:30, 1039–1044. <https://doi.org/10.1109/ICAICCIT60255.2023.10466092>

Bertoglio, R. (2021). The Digital Agricultural Revolution: A Bibliometric Analysis Literature Review. *IEEE Access*, 9(Query date: 2025-05-17 13:25:30), 134762–134782. <https://doi.org/10.1109/ACCESS.2021.3115258>

Cakir, L. V. (2023). Digital Twin Middleware for Smart Farm IoT Networks. *2023 International Balkan Conference on Communications and Networking, BalkanCom 2023*, Query date: 2025-05-17 13:25:30. <https://doi.org/10.1109/BalkanCom58402.2023.10167962>

Chandra, R. (2021). Digital agriculture for small-scale producers. *Communications of the ACM*, 64(12), 75–84. <https://doi.org/10.1145/3454008>

Chehri, A. (2020). A framework of optimizing the deployment of IoT for precision agriculture industry. *Procedia Computer Science*, 176(Query date: 2025-05-17 13:25:30), 2414–2422. <https://doi.org/10.1016/j.procs.2020.09.312>

Dahane, A. (2020). An IoT based smart farming system using machine learning. *2020 International Symposium on Networks, Computers and Communications, ISNCC 2020*, Query date: 2025-05-17 13:25:30. <https://doi.org/10.1109/ISNCC49221.2020.9297341>

Delgado, J. A. (2019). Big Data Analysis for Sustainable Agriculture on a Geospatial Cloud Framework. *Frontiers in Sustainable Food Systems*, 3(Query date: 2025-05-17 13:25:30). <https://doi.org/10.3389/fsufs.2019.00054>

Dey, K. (2021). Blockchain for sustainable e-agriculture: Literature review, architecture for data management, and implications. *Journal of Cleaner Production*, 316(Query date: 2025-05-17 13:25:30). <https://doi.org/10.1016/j.jclepro.2021.128254>

Dutta, G. (2020). Digital transformation priorities of India's discrete manufacturing SMEs – a conceptual study in perspective of Industry 4.0. *Competitiveness Review*, Query date: 2025-05-17 13:25:30, 289–314. <https://doi.org/10.1108/CR-03-2019-0031>

Frikha, T. (2023). Integrating blockchain and deep learning for intelligent greenhouse control and traceability. *Alexandria Engineering Journal*, 79(Query date: 2025-05-17 13:25:30), 259–273. <https://doi.org/10.1016/j.aej.2023.08.027>

Fuentes-Peñaillilo, F. (2024). Transformative Technologies in Digital Agriculture: Leveraging Internet of Things, Remote Sensing, and Artificial Intelligence for Smart Crop Management. *Journal of Sensor and Actuator Networks*, 13(4). <https://doi.org/10.3390/jsan13040039>

Goel, R. K. (2021). Smart agriculture – Urgent need of the day in developing countries. *Sustainable Computing: Informatics and Systems*, 30(Query date: 2025-05-17 13:25:30). <https://doi.org/10.1016/j.suscom.2021.100512>

Gómez-Chabla, R. (2019). IoT Applications in Agriculture: A Systematic Literature Review. *Advances in Intelligent Systems and Computing*, 901(Query date: 2025-05-17 13:25:30), 68–76. https://doi.org/10.1007/978-3-030-10728-4_8

Gupta, N. (2020). Economic data analytic AI technique on IoT edge devices for health monitoring of agriculture machines. *Applied Intelligence*, 50(11), 3990–4016. <https://doi.org/10.1007/s10489-020-01744-x>

Gurewitz, O. (2022). Data Gathering Techniques in WSN: A Cross-Layer View. *Sensors*, 22(7). <https://doi.org/10.3390/s22072650>

Hang, L. (2020). A secure fish farm platform based on blockchain for agriculture data integrity. *Computers and Electronics in Agriculture*, 170(Query date: 2025-05-17 13:25:30). <https://doi.org/10.1016/j.compag.2020.105251>

Javaid, M. (2022). Enhancing smart farming through the applications of Agriculture 4.0 technologies. *International Journal of Intelligent Networks*, 3(Query date: 2025-05-17 13:25:30), 150–164. <https://doi.org/10.1016/j.ijin.2022.09.004>

Khaleefah, R. M. (2023). Optimizing IoT Data Transmission in Smart Agriculture: A Comparative Study of Reduction Techniques. *HORA 2023 - 2023 5th International Congress on Human-Computer Interaction, Optimization and Robotic Applications, Proceedings*, Query date: 2025-05-17 13:25:30. <https://doi.org/10.1109/HORA58378.2023.10156757>

Leduc, G. (2021). Innovative blockchain-based farming marketplace and smart contract performance evaluation. *Journal of Cleaner Production*, 306(Query date: 2025-05-17 13:25:30). <https://doi.org/10.1016/j.jclepro.2021.127055>

Lima, G. C. (2020). Agro 4.0: Enabling agriculture digital transformation through IoT. *Revista Ciencia Agronomica*, 51(5). <https://doi.org/10.5935/1806-6690.20200100>

Lugonja, D. (2022). Smart Agriculture Development and Its Contribution to the Sustainable Digital Transformation of the Agri-Food Sector. *Tehnicki Glasnik*, 16(2), 264–267. <https://doi.org/10.31803/tg-20210914162640>

Lutta, P. (2021). The complexity of internet of things forensics: A state-of-the-art review. *Forensic Science International: Digital Investigation*, 38(Query date: 2025-05-17 13:25:30). <https://doi.org/10.1016/j.fsidi.2021.301210>

Masuda, Y. (2021). Internet of robotic things with digital platforms: Digitization of robotics enterprise. *Smart Innovation, Systems and Technologies*, 189(Query date: 2025-05-17 13:25:30), 381–391. https://doi.org/10.1007/978-981-15-5784-2_31

Mentsiev, A. U. (2020). IoT and mechanization in agriculture: Problems, solutions, and prospects. *IOP Conference Series: Earth and Environmental Science*, 548(3). <https://doi.org/10.1088/1755-1315/548/3/032035>

Onwude, D. I. (2020). Recent advances in reducing food losses in the supply chain of fresh agricultural produce. *Processes*, 8(11), 1–31. <https://doi.org/10.3390/pr8111431>

Pal, D. (2023). AI, IoT and Robotics in Smart Farming: Current Applications and Future Potentials. *2nd International Conference on Sustainable Computing and Data Communication Systems, ICSCDS 2023 - Proceedings, Query date: 2025-05-17 13:25:30, 1096–1101.* <https://doi.org/10.1109/ICSCDS56580.2023.10105101>

Rani, D. (2019). Implementation of an Automated Irrigation System for Agriculture Monitoring using IoT Communication. *Proceedings of IEEE International Conference on Signal Processing, Computing and Control, 2019* (Query date: 2025-05-17 13:25:30), 138–143. <https://doi.org/10.1109/ISPCC48220.2019.8988390>

Tholhappiyan, T. (2023). Agriculture Monitoring System with Efficient Resource Management using IoT. *Proceedings of the 2023 2nd International Conference on Augmented Intelligence and Sustainable Systems, ICAISS 2023, Query date: 2025-05-17 13:25:30, 1628–1633.* <https://doi.org/10.1109/ICAISS58487.2023.10250720>

Vasileiou, M. (2024). Transforming weed management in sustainable agriculture with artificial intelligence: A systematic literature review towards weed identification and deep learning. *Crop Protection, 176* (Query date: 2025-05-17 13:25:30). <https://doi.org/10.1016/j.cropro.2023.106522>

Xu, X. (2019). Design and implementation of cloud storage system for farmland internet of things based on NoSQL database. *Nongye Gongcheng Xuebao/Transactions of the Chinese Society of Agricultural Engineering, 35*(1), 172–179. <https://doi.org/10.11975/j.issn.1002-6819.2019.01.021>

Zgank, A. (2020). Bee swarm activity acoustic classification for an iot-based farm service. *Sensors (Switzerland), 20*(1). <https://doi.org/10.3390/s20010021>

Zhang, C. (2020). A deeply supervised image fusion network for change detection in high resolution bi-temporal remote sensing images. *ISPRS Journal of Photogrammetry and Remote Sensing, 166* (Query date: 2024-05-25 16:57:52), 183–200. <https://doi.org/10.1016/j.isprsjprs.2020.06.003>

Zhou, T. (2020). Design and Implementation of Agricultural Internet of Things System Based on Aliyun IoT Platform and STM32. *Journal of Physics: Conference Series, 1574*(1). <https://doi.org/10.1088/1742-6596/1574/1/012159>

Copyright Holder :

© Heri Setiyawan et.al (2024).

First Publication Right :

© Journal Ligundi of Community Service

This article is under:

