OPEN ACCESS
Global Journal of Research in Agriculture & Life Sciences
Volume 02| Issue 04 | July-Aug. | 2022
Journal homepage: https://gjrpublication.com/gjrals/

Original Research Article

An Organized Review of Current AI Trends for Smart Farming to Boost Crop Yield and Its Advantages

[1]Zaharadeen Yusuf Abdullahi, [2]Amira Musa Saad, [3]Salmanu Safiyanu Abdulsalam, [4]Kassim Sulaiman Abubakar, [4]Adamu Bello, [5]Muhammad Ahmad Baballe*

[1,3]Department of Agriculture Economics and Extension, Kano University of Science and Technology Wudil, Kano, Nigeria
[2]Department of Crop Science, Facaulty of Agriculture and Agricultural Technology, Kano University of Science and Technology Wudil, Kano, Nigeria
[4]Department of Electrical and Electronics Engineering Technology, School of Technology, Kano State Polytechnic, Kano, Nigeria
[5]Department of Computer Engineering Technology, School of Technology, Kano State Polytechnic, Kano, Nigeria

DOI: 10.5281/zenodo.7026553 **Submission Date:** 10th July 2022 | **Published Date:** 26th Aug. 2022

***Corresponding author:** Muhammad Ahmad Baballe

Abstract

At the moment, technology is being used extensively for development, one of which is the use of artificial intelligence (AI) to smart farming. Special powers can be programmed into artificial intelligence (AI) systems as needed. Artificial intelligence (AI), working with agricultural systems, helps to raise the standard of agriculture. The use of this technology in fundamental industries like agriculture is nothing new. Utilizing the most recent paper trends will help enhance agricultural yields in a variety of places. This is essential since there is a rising need for food sources and less land is accessible for agriculture. So, utilizing the features from the most recent year, this systematic review tries to gather the most recent trends in AI studies for Smart Farming publications.

Keywords: Smart Farming, Artificial Intelligence (AI), Crop Yield, Internet of Things (IoT), Wireless Sensor

Introduction

It is no longer strange if the world population can reach well above 9.1 billion people. It is possible that the need for food must have augmented by 69.9 percent, and the culture of moving people from rural to urban areas is likewise a topic of discussion. As the population rises, one can imagine if the land used for agriculture farming will experience a very severe deterioration in the years to come. The most significant reasons for reduced food production are inappropriate harvesting, improper planning, unpredictable weather conditions, irrigation techniques, and other matters such as livestock not being maintained [1]. But this can be aided by the advancement of technology. This progress will be momentously impacted if a common thread is drawn. Still, it cannot be equated altogether because small farmers and companies are left behind if they do not carry out digital transformation. As a new era of the Internet of Things emerges, several companies have seen how to stay ahead of the curve by leveraging open-source applications, low-cost sensors, and, more generally, scaled-up farmers and small businesses. Artificial intelligence (AI), in which an algorithm learns individually and contributes to the development of new insights, is also being discussed [2]. Of Things [3]–[6] has many research applications because it can be used in almost every technology. The up-to-date technology in intelligent systems, called "Smart Farming," usually utilizes the Internet of Things. It likewise offers hardware and software technology solutions to increase agricultural yields. Its enactment in agricultural land has altered over the past era, starting from using scissors and holes to cultivate fields and machines to harvest crops. Thus, Smart Farming was introduced because this method promises productivity in which farmers take advantage of the internet of things to be applied to all farming means and implementation methods [7]. Smart Farming [8]–[11] is broadly used in agriculture because it is very supportive. In intelligent surveys, each planted area had several criteria and could be measured for both quality and quantity. Some critical criteria for smart farming, such as nutrients [12], soil [13], pests [14], irrigation [15], determine the suitability and ability of certain types of crops. In most situations, different criteria usually exist in one crop field, let alone for the same crop growing on all available land for agriculture, because it requires a specific analysis of the location needed to map the production of plant products efficiently and effectively [16]. [17]-[21] is the most commonly used educational and academically. AI can likewise be called something that is artificial based on human intelligence. It is implanted in machines to be designed so that machines can think like humans. It is predictable to be able to do whatever living things do, so AI can be likened to learning to solve problems. Deep Learning (DL) and Machine Learning (ML) are part of AI, where ML is above DL. But it has the same function under artificial intelligence. This study becomes the main focus of their research. The AI methods can be applied in this field and combined with the internet of things and smart farming. These methods can be used to capture detailed and very complex information, after which artificial intelligence can provide good answers and suggestions for the problems being carried out [65]. Existing artificial intelligence methods include expert systems networks and fuzzy logic [22]. Machine learning [23-26] has been widely used to aid in the facilitation and resolution of problems. Other things can also take advantage of Deep Learning [27] – [30] in solving and easing imperative issues. Because DL and ML are part of Expert System Networks (AI), the author focuses on using them to solve systematic review problems that the author will display. Numerous instances of smart farming systems work on a combination of hardware and software to work optimally. One of the components that frequently exist in the internet of things is hardware [31-34]. Hardware has grown a lot because of support from internet of things (IoT) components. It can be carried anywhere, low power, with connections utilizing a wireless network to make connections between massive devices in large numbers. But don't forget to make use of the graphics processing unit (GPU) to be assisted by artificial intelligence. To collect artificial intelligence, information can use sensors to get input from the environment. This method is mostly done with the use of the internet. Big data technology aids this software, which aids in the collection of large amounts of data. The internet of things module can collect this data as input from several sources of information processed by sophisticated artificial intelligence-based software. As a result, AI can provide new decisions for farmers. This AI works very efficiently and effectively in studying the most recent trends [35]. Consequently, the need for smart farming, the internet of things, and artificial intelligence arises. Farmers often monitor and understand crops, which should be done for fieldwork. Hence, agriculture is always connected to equipment and uses that utilize artificial intelligence. The technology can be used from seeding to harvesting farm products. This likewise aids in timely harvest reports to minimize operational costs. Given that each country focuses on its own agricultural industry, we are waiting for the best solutions in technology with the hope of sustainable agriculture that does not cause environmental impacts. The newest communication and sensing technologies provide abilities for on-the-ground monitoring that are helpful for land pickers and farmers. These wireless sensors do an outstanding job of real-time crop monitoring with features like giving high accuracy and early detection of conditions on farmland. Applying these methods is not easy. Researchers, industry players, and the government put new hopes into increasing agricultural production with this latest technology, but this is not as easy as you think if you don't know the current trends in artificial intelligence for smart farming and how to improve the crop yield. Hence, it is essential to have an organized review and look at the current trends to see artificial intelligence and other AI methods that can be supported in Smart Farming systems. Numerous ways have been done in agriculture, such as measuring, monitoring, processing, and doing good marketing. Purushothaman and Terence [36] focus on smart farming methods and classify agricultural methods into IoT-based agricultural control and monitoring systems, automatic irrigation systems, and plant diseases. Research [37] has taken several into account: disease detection, plant classification, precision breeding, object recognition of pests, land cover identification, weed detection, smart irrigation, and phenotype. Other research, [38] focuses on agricultural research by conducting methodical reviews of future trends and challenges. These authors aim to conduct an efficient review of current trends using some of the artificial intelligence earlier studies appropriate for Smart Farming to improve crop yield. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) were proposed by researchers [39]. The modification to earlier studies is that the authors only concentrate on using PRISMA. The other purpose of this research comprises the publisher of the recent trends paper focusing on artificial intelligence for smart farming to improve crop yields. The country's present trends paper focuses on artificial intelligence for smart farming to improve crop yields. The contributions of this review are to: make a systematic review of artificial intelligence (AI) for smart farming to improve crop yield production; look for methods and platforms for artificial intelligence for smart farming to improve crop yields; and conduct discussions on the results that can be applied to a specific scope [65]. Many researchers must have analyzed the data from different viewpoints to determine which models are suitable. For instance, many uses of the Smart Farming focus show the fundamental openings and challenges of utilizing this novelty. This work aims to analyze Smart Farming using PRISMA by scientifically reviewing Smart Farming [40].

Fig. 1: The Smart Farming System of Today

DISCUSSSION

A. The Weather

The weather is an everyday thing that happens in agriculture. Their influence in the world of agriculture touches the performance of crop yields, so several studies are needed to aid artificial intelligence in understanding the weather in smart farming applications. Khanduja and Shandilya [41] said several studies have focused on weather, climate, and smart farming, but most research needs an important upsurge in funding. This research uses artificial intelligence in the weather. However, the study-specific SARIMAX algorithm was used to focus on artificial intelligence. Predictive analysis using Parvathi and Kamatchi [42] One of the AI methods, the Artificial Neural Network (ANN) method, has efficaciously performed the best crop analysis based on weather conditions. The ANN method is used in appropriate groupings for information mining and machine learning categorization. Jamil and Tarik [43] take an approach that utilizes artificial intelligence applied in agriculture. Using Convolutional Neural Networks (CNN) to stop the number of production results by taking advantage of the many weather and meteorological Then proceed to the information processing phase, such as segmentation, normalization, and filtering.

B. The Soil

In Smart Farming, it is inevitable to utilize the land. Smart Farming needs qualified and suitable soil to upsurge crop yield production. Suhag et al. [44] explained that there is no denying that farmers and landowners face challenges due to the ever-increasing population. One effective solution is to use new technologies such as the internet of things and AI. Thus, AI-assisted manufacturing has advanced a lot in farming methods, and all the tasks conducted by farmers have been made easier with AI. Technologies such as precision agriculture use AI technology for mapping diseases in crops, soil nutrition, and other challenges overcome by AI technology, especially robots, to harvest the crop production. Anand et al. [45] explained that monitoring nutrients in the soil is very significant because one of the effects is increasing agricultural yields and productivity, effectiveness and efficiency. Soil monitoring is based on basic parameters such as water content and temperature so that farmers can estimate the situation. One result of the right decisions being made is the choice of areas to plant to aid farmers or tillers. In this case, machine language (Hybrid algorithm) plays an important role in detecting the type of soil. Rodi et al. [46] explained the big role in the internet of things in terms of inputs that make the system smart in numerous things like digital and physical. As earlier explained, the intelligent system has not only provided a solution but efficiently assisted in the task of sensing soil moisture to ensure optimal water usage. With the aid of numerous other technologies, such as LoRa, can provide cost-effective and energy-efficient devices that have exceptional advantages over existing solutions. This research uses Long Short-Term Memory (LSTM). This algorithm is one of the deep learning ones. Reshma and colleagues [47] another breakthrough in agricultural land management, as previously described, can be improved by measuring soil characteristics. This information needs to be withdrawn and stored in the cloud and then re-analyzed on the land using artificial intelligence. So that farmers and land pickers can properly utilize resources and direct farming approaches wisely to optimize results. This research can use supervised learning like support vector machines (SVM) and decision trees to convey his recommendations.

C. The Irrigation

An imperative component of the increasing crop quality is the need for good water, one of which can be made from a good irrigation system. Goap et al. [48] The agriculture sector needs a lot of water for better crop yields, but freshwater supply is running low. This happens because the method used is conventional with many challenges, such as a lack of utilization of water use proficiency. In addition, there are a lot of climate and global warming changes that often impact the amount of rain intensity required to meet the availability. Supportable irrigation is one step in achieving food security. Algorithms using machine language (Support Vector Regression (SVR) + k-means) show fewer errors and improve accuracy. This method can be used to assist in making effective irrigation decisions. Kwok, Sun and [49], Technology in machine language can be used for learning and is very important in agriculture. In recent years, much research has taken advantage of machine learning as part of artificial intelligence. The utilization of deep learning in irrigation systems today is highly developed and developed by industry and research. Leveraging deeper and more specific learning with deep learning can adjust the water intensity on an irrigation system for the kinds of plants. Murthy and colleagues [50], Scheduling irrigation is very important, especially because traditional irrigation uses a lot of water, which causes incurable things such as water wastage and water pollution.

D. Unmanned Aerial Vehicle (UAV)

Rapid advances in technology make Smart Farming take advantage of it, one of which is UAVs, because it is unmanned and can be controlled anywhere. This section will discuss the application of AI-based UAVs that will aid Smart Farming. Psiroukis et al. [51] It is explained that broccoli is a plant that requires handling and is highly valued in agriculture and needs special care in the post-harvest and growing season. Broccoli heads are susceptible to damage because they are harvested by hand. In addition, it is first necessary to identify the land cultivation segment using Faster R-CNN and Center Net. Therefore, UAV research aims to automate architectural processing utilizing deep learning. Li et al. [52] conducted high-resolution result mapping to determine the pattern of spatial yield variability. In determining this, there are significant factors because it affects new insights and variability of management results in viewing agricultural products. In UAV, machine learning random forest regression (RFR) and SVR model approaches can improve the prediction of the results. A machine learning model can be used to perform different vegetation indications. Hoummaidi et al. [53] focus on supportable agriculture, which is the focus of food security. Some governments are starting to rely on new technology. Agricultural applications, likewise, depend on effective land monitoring. Nevertheless, in the traditional case, monitoring is carried out through field surveys, and it is very expensive, slow, and rare. By utilizing remote sensing using UAV drones, we can be efficient and not waste a lot of time on time-insensitive agricultural mapping [67].

E. Pest Control

All farmers nowadays comprehend that pests are enemies of the world of agriculture, especially in large numbers. By understanding such patterns and early detection, artificial intelligence can tackle pests. In this section, we will discuss how to focus on AI in reducing pests that will be applied to smart farming according to his research [54]. Agriculture is the primary food source. More than 91% of the population gets their food supply from agriculture in some countries. But there are glitches. One of these glitches is pests as a cause of reduced or lost crops in the agricultural world. Hence, technology is needed to classify pests that can aid in detecting pests, which is very significant to minimize pest movement. The experiment utilizes this proposed classification accuracy with different combinations of the learning rate, ResNeXt-50 (32 4d), information augmentation, and transfer learning. Hu et al. [55] demonstrate that deliberate knowledge about precise identification of pests has a significant role in deciding to control pests. According to him, it is essential to investigate the identification of pests in the field with characteristics such as their protective color, approaches for identifying pests based on YOLOv5 technology, and near-infrared imaging. Hung and Nam [56] found that highly toxic pests could negatively affect crop yields in the final phase and even product quality in the industry. Hence, everyone agrees to minimize pests and even wishes to detect the task of maximizing these crops to make decisions on minimizing the appropriate pests. Nevertheless, this has challenges, such as classifying insect species using the Deep Convolutional Neural Network (CNN), part of machine learning. Palaoag and Mique [57] focus on detecting rice diseases and pests and controlling and managing agricultural land attacked by these pests so that the crop yields. By utilizing this modern technology, pests and diseases are found in agriculture, especially in rice fields. This work focuses on finding suitable solutions and mechanisms for smallholder reporting. Utilizing image management and CNN, it is important to develop applications for detecting pests and diseases of rice.

F. The Weed Control

Weeds are considered very significant because they affect the nutrients present in the land. Other things can likewise affect agricultural yields from agricultural harvests. Reedha et al. [58] explained that controlling weeds and food crops is the mainstay of crop production and agriculture. Because, basically, these weeds take the same nutrients as plants. Consequently, weeds harm crop yield production if they cannot be controlled. Mapping and detection of weeds is a significant step. Utilizing the deep learning approach can provide good performance in many sensing tasks. In it, visual transformers (ViT) and UAV technology can help. Garibaldi-Márquez et al. [59] explicate that weed discrimination in the environment is challenging to overcome in smart farming practices, for instance, weed control. Many approaches are used. Developing a good practice system that recognizes weeds and their crops Its utilization is based on CNN and compared with the shallow learning approach. Razfar et al. [60] explicate if research focusing on weed detection is a part that is often used to implement Smart Farming in implementing the internet of things. Species such as weeds are responsible for 44.5% of crop losses due to the struggle for nutrients from native plants. Consequently, the weed detection method was used to reduce this percentage. This research focuses on detection methods using deep learning models to look for weeds in soybean plantations. The research used ResNet50, three custom CNN models, and MobileNetV2. Smart agriculture applications include identifying effective, accurate, and reliable weeds, controlling weed location, and proposing VGG16+SVM weed classification algorithms to optimize the algorithm. Ukaegbu et al. [62] explain that machine learning applications are very clear and are gaining more popularity. There are better algorithms, such as the deep learning algorithm for classification, signal identification, and crack detection. The deep learning algorithm has a wider application than other machine learning systems. The weed detection research CNN, using transfer learning focus in the earlier ResNet50 model, then proceeds to performance evaluation using random forest (RF).

G. The Disease Control

The plant diseases are becoming new material in the increased learning broadly to be studied systematically. Usually focuses on the biological characteristics of the disease. Recognizing plant diseases has recently been proven to require special attention. Early detection of disease can help maintain plant quality and crop production. Luna et al. [63] used tomato plants. In the ancient method of knowing the disease, an examination is carried out, and the treatment of the diseases in tomatoes is still done manually by practice. System development is needed to perform tasks such as detecting plant diseases for users so that they do not always do everything manually. There are general signs of damage such as fungal disease, bacterial, nematodes, and viruses originating, resulting in death on the underside of the leaf or yellowing and black spots on the bottom of the leaf. The research used in this study is from CNN. Anomalies were detected by F-RCNN trained to detect them. Afzaal et al. [64] other crops are likewise very susceptible to numerous diseases, which has led to an increase in the world of agriculture and industry. To improve the quality of plants, plants must protect plants from all kinds of harmful diseases. The available options include ancient ways to identify plant diseases to achieve this goal. This includes inspections carried out anciently or simply by prescribing disease. But this ancient technique was time-consuming, and not just anyone thought a disease had to be an expert. Other solutions such as using pesticides in crop production, only the use of chemical pesticides can be detrimental and cause poor food quality. On the other hand, farmers, likewise, need to increase labor costs. Thus, according to the author, early detection of plant diseases using Mask R-CNN architecture is essential to increase crop yields.

Impacts of Artificial Intelligence for Smart Farming to Enhance Crop Yield

1. To improve accuracy

The most talked-about benefits of smart farming are the improved levels of accuracy and precision that can be achieved. There is no one simple answer as to how much more precise Smart Farming is compared to traditional approaches, as the satellite auto guidance systems used in Smart Farming are available with different levels of pass-to-pass accuracy, ranging from +/-30 cm to +/-2 cm. Likewise, different tasks and implementations need different overlaps. For instance, manual steering while mowing results in overlaps of around 30 cm. With auto guidance such as Valtra Guide, this is reduced to just 5 cm. For fertilizer spreading, manual steering may give an overlap of about 4.5% on the headlands. With Valtra Guide and Section Control, the overlap can be reduced to 0%.

2. The increased work productivity means

The greatest thing about smart farming is its potential to save valuable time. Self-steering tractors use auto guidance software to automatically steer the tractor along way lines. Auto guidance software such as Valtra Guide can save up to 4.5% in time.

3. Improved fuel proficiency

Smart farming allows farmers to be much more precise. By reducing overlaps, it takes fewer passes to complete a task, hence tumbling the total distance the tractor is driven to get the job done. As well as saving time, this also saves fuel. Even reducing tasks like mowing by just one pass can have a cumulative effect over many hectares.

4. Reduced consumables

Farming by traditional means often results in significant under and over-application of sprays. Smart Farming technologies have the potential to decrease this by automatically switching off sections of the sprayer as the tractor meets the headland. Section Control by Valtra saves on average 4.5-10% of fertilizer costs by reducing overlaps to 0%. Different conditions call for different approaches. The soil and topography may vary across one field, meaning the requirement for spray or fertilizer may differ as well. Variable Rate Control automatically adjusts the flow of spray according to prescribed plans, making sure exactly the right amount of application is delivered to the right location. As well as reducing waste and costs, this also improves yields.

5. Increased yields

Over and under spraying affects the quality of the crop, leaving patchy areas of burnt plants and stunted, underperforming plants. By eradicating over and underlaps using Section Control, farmers can grow reliably even and healthy crops, maximizing yields. By using Valtra Guide when drilling, over-seeding is eradicated. Traditional farming methods rely on seed drills being manually turned on and off by the driver. This can lead to errors and areas being double drilled at the headland. When this happens, too many plants will try to grow in the same area, all competing for light, water, and nutrients. Certainly, this leads to a reduced yield in these areas.

6. Lower driver stress

Working long days and concentrating hard on maintaining straight lines whilst controlling implements can be stressful. The Smart farming can reduce the stresses of daily work in many ways. Auto guidance maintains a straight course, allowing the driver to focus on the implement and task at hand. Section Control takes all the guesswork out of switching the sprayer on and off.

7. Ease of use

The Smart Farming implements use ISOBUS connection, which means any implement can be connected to the tractor with 'plug and play' ease of use. Simply connect the implement, plug in the ISOBUS, and you're good to go! The Valtra Smart Touch armrest can control Smart Farming technologies from a simple touchscreen and joystick interface that is easier to use than a smartphone. Because all functions are controlled by this one simple device, there is no need for training on multiple devices and interfaces.

8. Easier recording and reporting

Maintaining logs, recording tasks, and reporting can take time but is not always the most rewarding task. With Smart Farming, tasks are automatically recorded and can be transferred wirelessly. By automating the collection and transfer of information using a Farm Management Information System (FMIS), you can be sure all your records are up-to-date and precise.

9. Easier financial forecasting

By handling all this data centrally from FMIS software, it is easy to see how long tasks take, how much fuel and inputs are needed, and how much plans cost. With smart telemetry systems like Valtra Connect, it is even possible to send diagnostic information to service partners to plan maintenance needs in advance, preventing unscheduled downtime.

10. Improved sustainability

There are many ways that smart farming can improve sustainability. From reducing spray wastage to improving fuel economy. By reducing the number of passes needed to complete tasks and reducing turning on the headland, soil compaction is minimized [66].

Conclusion

This work focuses on performing a thorough analysis of recent developments in crop yield-improving publications using artificial intelligence for smart farming. This evaluation aids in identifying the most recent developments in crop yield enhancement technology. I also examine a number of aspects like weather, soil, irrigation, unmanned aerial vehicles (UAV), insect control, weed control, and disease control that can improve agricultural yields. On the other hand, these AI-related aspects have a big impact on how well smart farming works. Other approaches, such as statistical models, system recommenders, and multi-agent systems, can be used to review more research. The effects of intelligent farming systems are also covered.

References

1. Sharma, A. Jain, P. Gupta, and V. Chowdary, "Machine Learning Applications for Precision Agriculture: A Comprehensive Review," IEEE Access, vol. 9, pp. 4843–4873, 2021, doi: 10.1109/ACCESS.2020.3048415.
2. R. Dolci, "IoT Solutions for Precision Farming and Food Manufacturing: Artificial Intelligence Applications in Digital Food," in 2017 IEEE 41st Annual Computer Software and Applications Conference (COMPSAC), Jul. 2017, pp. 384–385. doi: 10.1109/COMPSAC.2017.157.
3. M. H. Widianto, T. E. Suherman, and J. Chiedi, "Pathfinding Augmented Reality for Fire Early Warning IoT Escape Purpose," International Journal of Engineering Trends and Technology, vol. 69, no. 7, pp. 190–197, 2021, doi: 10.14445/22315381/IJETT V69I7P226.
4. M. H. Widianto, A. Ramadhan, A. Trisetyarso, and E. Abdurachman, "Energy saving on IoT using LoRa: a systematic literature review," International Journal of Reconfigurable and Embedded Systems (IJRES), vol. 11, no. 1, pp. 25–33, Mar. 2022, doi: 10.11591/ijres.v11.i1.pp25-33.
5. R. Yu, X. Zhang, and M. Zhang, "Smart Home Security Analysis System Based on The Internet of Things," in 2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE), Mar. 2021, pp. 596–599. doi: 10.1109/ICBAIE52039.2021.9389849.
6. Huang, "Architecture of Audio Broadcasting Coverage Monitoring System Based on Internet of Things," in 2019 IEEE International Conference on Smart Internet of Things (SmartIoT), Aug. 2019, pp. 320–324. doi: 10.1109/SmartIoT.2019.00055.
7. G. Idoje, T. Dagiuklas, and M. Iqbal, "Survey for smart farming technologies: Challenges and issues," Computers & Electrical Engineering, vol. 92, p. 107104, 2021, doi: 10.1016/j.compeleceng.2021.107104.

8. M. S. D. Abhiram, J. Kuppili, and N. A. Manga, “Smart Farming System using IoT for Efficient Crop Growth,” in 2020 IEEE International Students’ Conference on Electrical,Electronics and Computer Science (SCEECS), Feb. 2020, pp. 1–4. doi: 10.1109/SCEECS48394.2020.147.
9. F. Nolack Fote, S. Mahmoudi, A. Roukh, and S. Ahmed Mahmoudi, “Big Data Storage and Analysis for Smart Farming,” in 2020 5th International Conference on Cloud Computing and Artificial Intelligence: Technologies and Applications (CloudTech), Nov. 2020, pp. 1–8. doi: 10.1109/CloudTech49835.2020.9365869.
10. X. Jiang et al., “Wireless Sensor Network Utilizing Flexible Nitrate Sensors for Smart Farming,” in 2019 IEEE SENSORS, Oct. 2019, pp. 1–4. doi: 10.1109/SENSORS43011.2019.8956915.
11. R. Deepa, V. Moorthy, R. Venkataraman, and S. S. Kundu, “Smart Farming Implementation using Phase based IOT System,” in 2020 International Conference on Communication and Signal Processing (ICCSP), Jul. 2020, pp. 930–934. doi: 10.1109/ICCSP48568.2020.9182078.
12. B. Ban, J. Lee, D. Ryu, M. Lee, and T. D. Eom, “Nutrient Solution Management System for Smart Farms and Plant Factory,” in 2020 International Conference on Information and Communication Technology Convergence (ICTC), Oct. 2020, pp. 1537–1542. doi: 10.1109/ICTC49870.2020.9289192.
13. L. Yu et al., “Comprehensive Evaluation of Soil Moisture Sensing Technology Applications Based on Analytic Hierarchy Process and Delphi,” Agriculture, vol. 11, no. 11, p. 1116, Nov. 2021, doi: 10.3390/agriculture11111116.
14. H. Nasir, A. N. Aris, A. Lajis, K. Kadir, and S. I. Safie, “Development of Android Application for Pest Infestation Early Warning System,” in 2018 IEEE 5th International Conference on Smart Instrumentation, Measurement and Application (ICSIMA), Nov. 2018, pp. 1–5. doi: 10.1109/ICSIMA.2018.8688774.
15. A. Cabarcas, C. Arrieta, D. Cermeño, H. Leal, R. Mendoza, and C. Rosales, “Irrigation System for Precision Agriculture Supported in the Measurement of Environmental Variables,” in 2019 7th International Engineering, Sciences and Technology Conference (IESTEC), Oct. 2019, pp. 671–676. doi: 10.1109/IESTEC46403.2019.00125.
16. M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour, and E.-H. M. Aggoune, “Internet-of-Things (IoT)-Based Smart Agriculture: Toward Making the Fields Talk,” IEEE Access, vol. 7, pp. 129551– 129583, 2019, doi: 10.1109/ACCESS.2019.2932609.
17. H. WANG, Y. LIU, Z. HAN, and J. WU, “Extension of media literacy from the perspective of artificial intelligence and implementation strategies of artificial intelligence courses in junior high schools,” in 2020 International Conference on Artificial Intelligence and Education (ICAIE), Jun. 2020, pp. 63–66. doi: 10.1109/ICAIE50891.2020.00022.
18. Z. Li, “Analysis on the Influence of Artificial Intelligence Development on Accounting,” in 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE), Jun. 2020, pp. 260–262. doi: 10.1109/ICBAIE49996.2020.00061.
19. X. Fu, “The Application of Artificial Intelligence Technology in College Physical Education,” in 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE), Jun. 2020, pp. 263–266. doi: 10.1109/ICBAIE49996.2020.00062.
20. N. Wang, Y. Liu, Z. Liu, and X. Huang, “Application of Artificial Intelligence and Big Data in Modern Financial Management,” in 2020 International Conference on Artificial Intelligence and Education (ICAIE), Jun. 2020, pp. 85–87. doi: 10.1109/ICAIE50891.2020.00027.
21. S. Zel and E. Kongar, “Transforming Digital Employee Experience with Artificial Intelligence,” in 2020 IEEE / ITU International Conference on Artificial Intelligence for Good (AI4G), Sep. 2020, pp. 176–179. doi: 10.1109/AI4G50087.2020.9311088. [22] R. Sharma, “Artificial Intelligence in Agriculture: A Review,” in 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), May 2021, pp. 937–942. doi: 10.1109/ICICCS51141.2021.9432187.
22. K. Pahwa and N. Agarwal, “Stock Market Analysis using Supervised Machine Learning,” in 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), Feb. 2019, pp. 197–200. doi: 10.1109/COMITCon.2019.8862225.
23. Q. Zhao, J. Sun, H. Ren, and G. Sun, “Machine-Learning Based TCP Security Action Prediction,” in 2020 5th International Conference on Mechanical, Control and Computer Engineering (ICMCCE), Dec. 2020, pp. 1329–1333. doi: 10.1109/ICMCCE51767.2020.00291.
24. J. Ma, “Machine Learning in Predicting Diabetes in the Early Stage,” in 2020 2nd International Conference on Machine Learning, Big Data and Business Intelligence (MLBDBI), Oct. 2020, pp. 167–172. doi: 10.1109/MLBDBI51377.2020.00037.
25. N. Li, T. Zong, and Z. Zhang, “Prediction of the Electronic Work Function by Regression Algorithm in Machine Learning,” in 2021 IEEE 6th International Conference on Big Data Analytics (ICBDA), Mar. 2021, pp. 87–91. doi: 10.1109/ICBDA51983.2021.9403202.
26. H. C. Kaskavalci and S. Gören, “A Deep Learning Based Distributed Smart Surveillance Architecture using Edge and Cloud Computing,” in 2019 International Conference on Deep Learning and Machine Learning in Emerging Applications (Deep-ML), Aug. 2019, pp. 1–6. doi: 10.1109/Deep-ML.2019.00009.

27. H. S. DIKBAYIR and H. İbrahim BÜLBÜL, “Deep Learning Based Vehicle Detection From Aerial Images,” in 2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA), Dec. 2020, pp. 956–960. doi: 10.1109/ICMLA51294.2020.00155.
28. N. Shen, “A Deep Learning Approach of English Vocabulary for Mobile Platform,” in 2021 13th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA), Jan. 2021, pp. 463–466. doi: 10.1109/ICMTMA52658.2021.00106.
29. A. Karami, M. Crawford, and E. J. Delp, “A Weakly Supervised Deep Learning Approach for Plant Center Detection and Counting,” in IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, Sep. 2020, pp. 1584–1587. doi: 10.1109/IGARSS39084.2020.9324354.
30. I. Tudosa, F. Picariello, E. Balestrieri, L. de Vito, and F. Lamonaca, “Hardware Security in IoT era: the Role of Measurements and Instrumentation,” in 2019 II Workshop on Metrology for Industry 4.0 and IoT (MetroInd4.0 IoT), Jun. 2019, pp. 285–290. doi: 10.1109/METROI4.2019.8792895.
31. W. Shalannanda, I. Zakia, F. Fahmi, and E. Sutanto, “Implementation of the Hardware Module of IoT-based Infant Incubator Monitoring System,” in 2020 14th International Conference on Telecommunication Systems, Services, and Applications (TSSA, Nov. 2020, pp. 1–5. doi: 10.1109/TSSA51342.2020.9310901.
32. H. Tao, M. Z. A. Bhuiyan, A. N. Abdalla, M. M. Hassan, J. M. Zain, and T. Hayajneh, “Secured Data Collection With Hardware-Based Ciphers for IoT-Based Healthcare,” IEEE Internet of Things Journal, vol. 6, no. 1, pp. 410–420, Feb. 2019, doi: 10.1109/JIOT.2018.2854714.
33. H. Q. T. Ngo, T. P. Nguyen, and H. Nguyen, “Hardware Design for Intelligent IoT Approach to Optimize Parking Slots,” in 2019 International Conference on Advanced Computing and Applications (ACOMP), Nov. 2019, pp. 171–175. doi: 10.1109/ACOMP.2019.00034.
34. S. Qazi, B. A. Khawaja, and Q. U. Farooq, “IoT-Equipped and AI Enabled Next Generation Smart Agriculture: A Critical Review, Current Challenges and Future Trends,” IEEE Access, vol. 10, pp. 21219–21235, 2022, doi: 10.1109/ACCESS.2022.3152544.
35. S. Terence and G. Purushothaman, “Systematic Review of Internet of Things in Smart Farming,” Trans. Emerg. Telecommun. Technol., vol. 31, no. 6, Jun. 2020, doi: 10.1002/ett.3958.
36. Z. Ünal, “Smart Farming Becomes even Smarter with Deep Learning - A Bibliographical Analysis,” IEEE Access, vol. 8, pp. 105587– 105609, 2020, doi: 10.1109/ACCESS.2020.3000175.
37. E. Navarro, N. Costa, and A. Pereira, “A Systematic Review of IoT Solutions for Smart Farming,” Sensors, vol. 20, no. 15, p. 4231, Jul. 2020, doi: 10.3390/s20154231.
38. D. Moher, A. Liberati, J. Tetzlaff, and D. G. Altman, “Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement,” J Clin Epidemiol, vol. 62, no. 10, pp. 1006– 1012, 2009, doi: 10.1016/j.jclinepi.2009.06.005. [
39. W. S. Alaloul, M. Altaf, M. A. Musarat, M. F. Javed, and A. Mosavi, “Systematic Review of Life Cycle Assessment and Life Cycle Cost Analysis for Pavement and a Case Study,” Sustainability, vol. 13, no. 8, p. 4377, Apr. 2021, doi: 10.3390/su13084377.
40. U. Shandilya and V. Khanduja, “Intelligent Farming System With Weather Forecast Support and Crop Prediction,” in 2020 5th International Conference on Computing, Communication and Security (ICCCS), Oct. 2020, pp. 1–6. doi: 10.1109/ICCCS49678.2020.9277437.
41. S. B. Kamatchi and R. Parvathi, “Improvement of Crop Production Using Recommender System by Weather Forecasts,” Procedia Computer Science, vol. 165, pp. 724–732, 2019, doi: 10.1016/j.procs.2020.01.023.
42. H. Tarik and O. M. Jamil, “Weather Data For The Prevention Of Agricultural Production With Convolutional Neural Networks,” in 2019 International Conference on Wireless Technologies, Embedded and Intelligent Systems (WITS), Apr. 2019, pp. 1–6. doi: 10.1109/WITS.2019.8723765.
43. S. Suhag, N. Singh, S. Jadaun, P. Johri, A. Shukla, and N. Parashar, “IoT based Soil Nutrition and Plant Disease Detection System for Smart Agriculture,” in 2021 10th IEEE International Conference on Communication Systems and Network Technologies (CSNT), Jun. 2021, pp. 478–483. doi: 10.1109/CSNT51715.2021.9509719.
44. R. Anand, D. Sethi, K. Sharma, and P. Gambhir, “Soil Moisture and Atmosphere Components Detection System Using IoT and Machine Learning,” in 2019 International Conference on Smart Systems and Inventive Technology (ICSSIT), Nov. 2019, pp. 842–847. doi: 10.1109/ICSSIT46314.2019.8987754.
45. L. D. Rodić, T. Županović, T. Perković, P. Šolić, and J. J. P. C. Rodrigues, “Machine Learning and Soil Humidity Sensing: Signal Strength Approach,” ACM Trans. Internet Technol., vol. 22, no. 2, Oct. 2021, doi: 10.1145/3418207.
46. R. Reshma, V. Sathiyavathi, T. Sindhu, K. Selvakumar, and L. SaiRamesh, “IoT based Classification Techniques for Soil Content Analysis and Crop Yield Prediction,” in 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Oct. 2020, pp. 156–160. doi: 10.1109/I SMAC49090.2020.9243600.
47. A. Goap, D. Sharma, A. K. Shukla, and C. Rama Krishna, “An IoT based smart irrigation management system using Machine learning and open source technologies,” Computers and Electronics in Agriculture, vol. 155, pp. 41–49, 2018, doi: 10.1016/j.compag.2018.09.040.

48. J. Kwok and Y. Sun, "A Smart IoT-Based Irrigation System with Automated Plant Recognition Using Deep Learning," in Proceedings of the 10th International Conference on Computer Modeling and Simulation, 2018, pp. 87–91. doi: 10.1145/3177457.3177506.
49. A. Murthy, C. Green, R. Stoleru, S. Bhunia, C. Swanson, and T. Chaspari, "Machine Learning-Based Irrigation Control Optimization," in Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, 2019, pp. 213–222. doi: 10.1145/3360322.3360854.
50. V. Psiroukis, B. Espejo-Garcia, A. Chitos, A. Dedousis, K. Karantzalos, and S. Fountas, "Assessment of Different Object Detectors for the Maturity Level Classification of Broccoli Crops Using UAV Imagery," Remote Sensing, vol. 14, no. 3, p. 731, Feb. 2022, doi: 10.3390/rs14030731.
51. D. Li et al., "Improving Potato Yield Prediction by Combining Cultivar Information and UAV Remote Sensing Data Using Machine Learning," Remote Sensing, vol. 13, no. 16, p. 3322, Aug. 2021, doi: 10.3390/rs13163322.
52. L. el Hoummaidi, A. Larabi, and K. Alam, "Using unmanned aerial systems and deep learning for agriculture mapping in Dubai," Heliyon, vol. 7, no. 10, p. e08154, 2021, doi: 10.1016/j.heliyon.2021.e08154.
53. C. Li, T. Zhen, and Z. Li, "Image Classification of Pests with Residual Neural Network Based on Transfer Learning," Applied Sciences, vol. 12, no. 9, p. 4356, Apr. 2022, doi: 10.3390/app12094356.
54. Z. Hu et al., "Research on Identification Technology of Field Pests with Protective Color Characteristics," Applied Sciences, vol. 12, no. 8, p. 3810, Apr. 2022, doi: 10.3390/app12083810.
55. N. T. Nam and P. D. Hung, "Pest Detection on Traps Using Deep Convolutional Neural Networks," in Proceedings of the 2018 International Conference on Control and Computer Vision, 2018, pp. 33–38. doi: 10.1145/3232651.3232661.
56. E. L. Mique and T. D. Palaoag, "Rice Pest and Disease Detection Using Convolutional Neural Network," in Proceedings of the 2018 International Conference on Information Science and System, 2018, pp. 147–151. doi: 10.1145/3209914.3209945.
57. R. Reedha, E. Dericquebourg, R. Canals, and A. Hafiane, "Transformer Neural Network for Weed and Crop Classification of High Resolution UAV Images," Remote Sensing, vol. 14, no. 3, p. 592, Jan. 2022, doi: 10.3390/rs14030592.
58. F. Garibaldi-Márquez, G. Flores, D. A. Mercado-Ravell, A. Ramírez Pedraza, and L. M. Valentín-Coronado, "Weed Classification from Natural Corn Field-Multi-Plant Images Based on Shallow and Deep Learning," Sensors, vol. 22, no. 8, p. 3021, Apr. 2022, doi: 10.3390/s22083021.
59. N. Razfar, J. True, R. Bassiouny, V. Venkatesh, and R. Kashef, "Weed detection in soybean crops using custom lightweight deep learning models," Journal of Agriculture and Food Research, vol. 8, p. 100308, 2022, doi: 10.1016/j.jafr.2022.100308.
60. J. Haichen, C. Qingrui, and L. Zheng Guang, "Weeds and Crops Classification Using Deep Convolutional Neural Network," in 2020 the 3rd International Conference on Control and Computer Vision, 2020, pp. 40–44. doi: 10.1145/3425577.3425585.
61. U. F. Ukaegbu, L. K. Tartibu, M. O. Okwu, and I. O. Olayode, "Deep Learning Application in Diverse Fields with Plant Weed Detection as a Case Study," in Proceedings of the International Conference on Artificial Intelligence and Its Applications, 2021, pp. 1–9. doi: 10.1145/3487923.3487926.
62. R. G. de Luna, E. P. Dadios, and A. A. Bandala, "Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition," in TENCON 2018 - 2018 IEEE Region 10 Conference, Oct. 2018, pp. 1414–1419. doi: 10.1109/TENCON.2018.8650088.
63. U. Afzaal, B. Bhattarai, Y. R. Pandeya, and J. Lee, "An Instance Segmentation Model for Strawberry Diseases Based on Mask R-CNN," Sensors, vol. 21, no. 19, p. 6565, Sep. 2021, doi: 10.3390/s21196565.
64. M. H. Widianto, M. I. Ardimansyah, H. I. Pohan, D. R. Hermanus, "A Systematic Review of Current Trends in Artificial Intelligence for Smart Farming to Enhance Crop Yield", Journal of Robotics and Control (JRC), Vol. 3, No. 3, , DOI: 10.18196/jrc.v3i3.13760, pp. 269-278, May 2022.
65. https://www.valtra.com/blog/technology/the-top-ten-benefits-of-smart-farming.html
66. M. A. Baballe, M. I. Bello, A. U. Alkali, Z. Abdulkadir, A. S. Muhammad, F. Muhammad, "The Unmanned Aerial Vehicle (UAV): Its Impact and Challenges", Global Journal of Research in Engineering & Computer Sciences, Vol. 02, No 03, Journal homepage: https://gjrpublication.com/gjrecs/, pp. 35-39, May-June | 2022.

CITE AS

Zaharadeen Yusuf Abdullahi, Amira Musa Saad, Salmanu Safiyanu Abdulsalam, Kassim Sulaiman Abubakar, Adamu Bello, & Muhammad Ahmad Baballe. (2022). An Organized Review of Current AI Trends for Smart Farming to Boost Crop Yield and Its Advantages. Global Journal of Research in Agriculture & Life Sciences, 2(4), 6–14. https://doi.org/10.5281/zenodo.7026553