



Artificial Intelligence (AI) in Agricultural Farming Systems: Benefits and Challenges

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Abstract

Artificial intelligence (AI) is transforming agriculture through digital agriculture or smart farming, enhancing productivity and efficiency. Integrating AI with agricultural practices, we can increase crop yields and address global food challenges. This systematic review synthesizes the latest trends in AI research for smart farming, highlighting recent technological advancement of the fourth industrial revolution and applications. Furthermore, we discussed the positive and the negative aspects of AI in agriculture farming systems, providing a comprehensive overview of its role in shaping the future of agriculture.

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

I. INTRODUCTION

It is no longer strange if the world population can reach well above 9.1 billion people by 2050. 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]. However, this can be aided by the advancement of technology. This progress will be momentarily 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 educationally and academically. 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 authors focus 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. However, 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, however, 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 recognition, 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, there are several 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].

II. DISCUSSION

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 weathers 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.

III. 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].

IV. DRAWBACKS OF AI IN AGRICULTURE SYSTEMS

Although AI promises significant improvements, its application in agriculture also presents some difficulties or unfavorable effects of technology on agriculture, such as:

1. High Initial Investment

AI technology use in agriculture necessitates a large upfront cost. Small-scale farmers may face financial hardships when it comes to the acquisition and integration of AI-driven equipment, systems, and infrastructure. To effectively implement these technologies, farmers may need to make investments in sensors, drones, AI-driven gear, and infrastructural changes. Budgets may be further strained by the expenses of employing and training qualified staff members who can operate these complex systems.

2. A Long Technology Adoption Process

One potential obstacle to AI implementation in agriculture is the sometimes-protracted adoption process of new technologies. Farmers will need some time to adjust to this shift in order to comprehend the operation of contemporary technology and successfully integrate them into their current systems. Further delaying the adoption process is the possibility that certain AI solutions have a learning curve due to their complexity.

3. Data Privacy and Security

Data analysis and collecting are critical components of AI systems. There are worries about critical agricultural data security and privacy. These data's use and storage exposes them to cybersecurity risks such malicious attacks, illegal access, and data breaches. Sensitive information about farmers and agricultural enterprises needs to be protected from theft, manipulation, and abuse. Strict privacy laws, strong cybersecurity safeguards, and moral data processing procedures are needed for this component in order to protect sensitive agricultural data.

4. Job Displacement

Agricultural workers may lose their jobs as a result of the automation and mechanization of AI technology in farming. Employment in rural areas may be impacted by a decline in the need for manual labor as jobs become more mechanized. There will be less need for physical work in farming as AI-powered equipment and robots can handle jobs like planting, harvesting, and monitoring. The lives of agricultural laborers, especially those in repetitive and routine jobs, may be negatively impacted by this change.

5. Environmental Concerns

Although AI maximizes the use of resources, relying too much on AI-driven agricultural techniques may have unexpected negative effects on the environment. When technology is used excessively, it can result in higher energy costs, waste from out-of-date equipment, or even the disregard for conventional sustainable practices.

6. Technological Dependence

Farmers that rely too much on AI for management and decision-making on their farms may become dependent on technology. Farmers who heavily depend on AI systems may have difficulties if these devices break down, have outages, or have technical problems [67].

CONCLUSION

The main goal of this work is to conduct a comprehensive analysis of current advancements in publications that employ artificial intelligence (AI) for smart farming to increase crop productivity. The most recent advancements in crop yield enhancement technology are identified with the help of this evaluation. In order to increase agricultural yields, we also look at a variety of factors like the weather, soil, irrigation, unmanned aerial vehicles, insect, weed, and disease control. Conversely, these AI-related factors significantly influence the efficacy of smart farming [64]. To review further research, alternative methods including statistical models, system recommenders, and multi-agent systems might be employed. There is also discussion on the impacts of intelligent farming systems [68].

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