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Automation Techniques for Smart and Sustainable Agriculture and its Challenges

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Abstract. In the contemporary scenario, the world is primarily focused on trends and technology that leads to intelligent and accurate results in every field. Automation of everything has come up as a necessary demand due to this reason. Things are automated wherever possible. Agriculture is also one such field where automation has acquired much popularity. With the advent of the Fourth Industrial Revolution, integration of various tools and technologies like IoT, Deep Learning, cloud, etc., has led to the development of several automated agriculture systems, generally termed as "Smart and Sustainable Agriculture". Motivated by this fact, a comparative study of state-of-the-art approaches for Smart and Sustainable Agriculture systems using automated devices is presented in this paper. To build the basics, the paper discusses the Smart and Sustainable agriculture systems techniques for the automation of the agriculture systems. The next section presents the relative performance of different approaches. At last, the upcoming challenges and future work directions in this field are discussed next.

Keywords: Sustainable Agriculture, Automation, Agroforestry, Smart Irrigation, Smart Cropping.

1. Introduction

Agriculture [1] is treated as the backbone for any country as it is one of the significant aspects in improving economic growth. The traditional agriculture system needs manual monitoring continuously. Farmers may not be available full-time to monitor them. Thus, automated systems based on the Internet of Things (IoT) [2], image/digital vision [3] based monitoring systems are required for efficient crop cultivation. Agriculture automation [4] is playing a key role in every country's development. Computer Vision is one such field of research that makes this possible, i.e., it makes the machine see, think, and perform spontaneous actions as per the requirement. It uses cameras and some high-level processing units to capture the images, tract/identify the problem and generate action accordingly within less time. Aerial Imagery has been extensively used for the past few years for crop monitoring and research. Huge sets of images and videos are collected through these cameras from the field, and machine learning techniques are applied to make appropriate and reliable decisions. Moreover, every day the technology upgrades, so more efficient automated systems must be designed with the latest technological

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advancements to handle large-scale agriculture data. Thus, it is recommended to use and integrate Deep Learning (DL) [5] and Machine Learning (ML) techniques with computer vision. Drone cameras can be used to monitor the activities of the crop to manage the moisture of soil, species classification, water management, crop quality, prediction of yield, leaf disease detection, weed detection, etc. IoT-based systems are also being used for the last five years to increase productivity with less workforce (i.e., via remote controlling). These IoT-based systems develop massive amounts of data both in images and text daily. Processing or analysing this large-scale data of images and text needs different approaches since their data type formats are different and storage models are also different. Data mining [6] techniques, ML and DL techniques are becoming necessary for handling big data models. Incorporating these latest technologies, some software apps and tools are being developed these days to make farmers' lives easy. These apps reduce the time delay in identifying the actual problems of cultivation like climate conditions, leaf disease patterns, soil and water management, etc. The process of smart agriculture consists of three steps: data collection, decision making, and intervention as depicted in Fig. 1. In data collection phase, sensors are utilized to collect data from different sources. In decision making, different technologies such as Machine Learning, IoT, Deep Learning, Expert Systems, etc. are used to take decisions for the better cultivation of crops and also reduces the human intervention. In third phase, intelligent systems such as robots, automated surveillance systems, etc. are deployed for field operations. Thus, the present paper analyses and summarizes the latest advancements in developing automated smart and sustainable agriculture systems.

The section 1 of the present papers confers the brief overview of the agriculture automation. The remaining paper is structured as; usage of different techniques such as Computer Vision, IoT, Robotics are reviewed in section 2. Section 3 highlights the research gaps of the smart automation followed by the conclusion and future prospect in section 4.

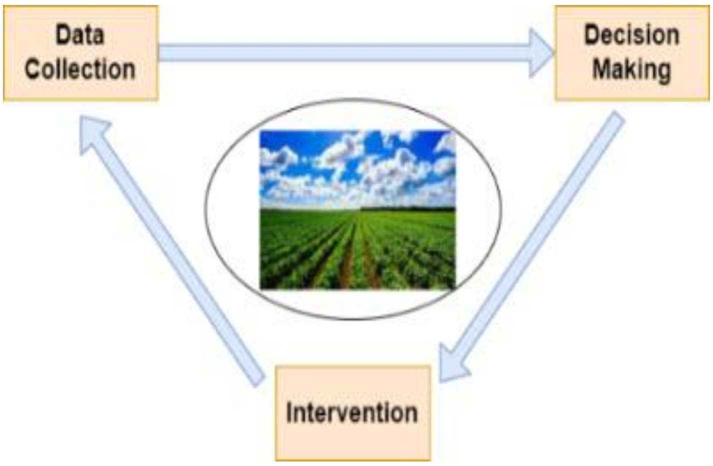

Figure 1. Process of smart agriculture.

2. Use of computer vision, lot, cloud, and robotics in smart and sustainable agricultural automation

A good amount of exploration has been done in the domain of agricultural automation in which different technologies such as image processing, computer vision, IoT, cloud computing, and robotics play a prominent role as shown in Fig. 2.

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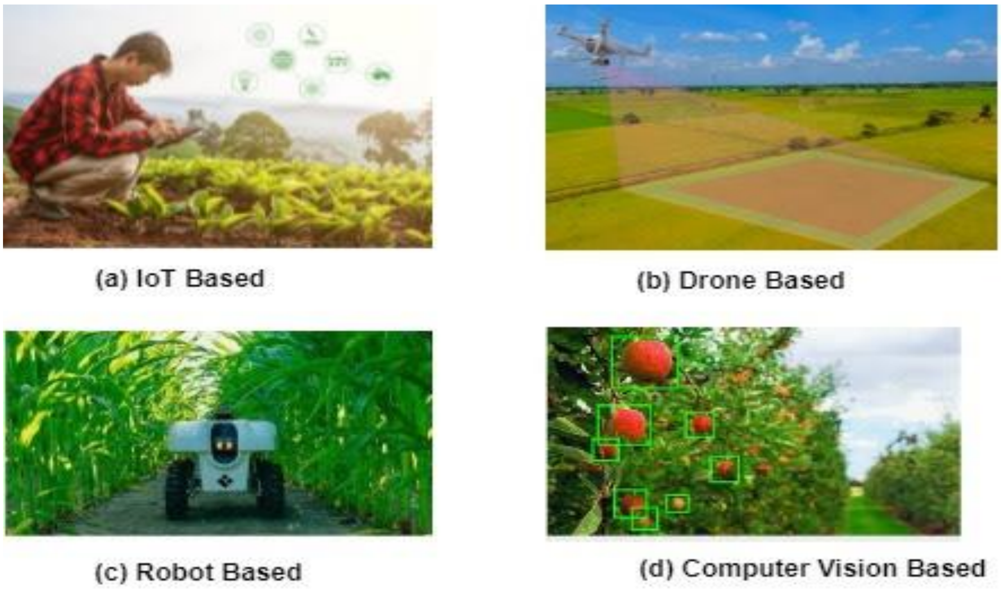

Figure 2. Smart and sustainable agriculture system a) IoT-based, b) Drone-based, c) Robot-based d) Computer Vision-based.

2.1. Computer Vision and Image Processing for Agricultural Automation

Machine and Deep learning techniques have seen encouraging growth in recent times. This increase in the growth of interest is primarily linked to the growth in the processing units of computer devices. Machine learning / Deep learning is a class of artificial intelligence that emulates a connectionist technique inspired by the working of the neurons in human brains [7]. These connections are modelled in numerical representations called vectors (more recently tensors). Processing of these vectors is done sequentially, and this means that if the vectors are large (connections are deep) or if it requires a complex mathematical operation, it may take a longer time to complete the processing. This setback discourages many researchers from venturing into exploring the neural network. Graphical Processing Unit (GPU) has recently provided an option that has encouraged researchers to revisit these technologies. GPUs can process data/vectors in parallel, which speeds up the overall processing time required. Therefore, with a large amount of data, GPUs enable Deep Neural networks (DNNs) to act like the complex neurons in a human brain [8].

The usage of Artificial Intelligence (AI) and Computer Vision (CV) in the agriculture and food industry is illustrated in Fig. 3 in detail [9]. Machine and Deep learning have come a long way in industrial and research applications across many fields, ranging from medicine, bioinformatics, art, gaming, agriculture, and many more. However, it is still far away from reaching its goal. Computer vision is another technology of AI to use Machine or Deep learning that started with how to recreate and understand human perception through camera schematics, photogrammetry, and projections in the early 1960s [10]. Agriculture is one of the many fields that have benefitted from the growth of deep learning techniques. Agricultural products are characterized by several factors such as weather, water, soil topography, and nutrients, and more. Measuring all these factors is essential for predicting and controlling any adversaries that may affect agricultural products' productions. With the increasing growth of available digital data, exploring Machine or Deep learning techniques can find practical applicability in this area. Like in [11-13] where Machine-learning techniques have been exploited to combat food security issues by predicting or proposing solutions to existing challenges faced across the world. Machine or Deep learning techniques used to influence the growth of agricultural practices are referred to as Smart Agriculture.

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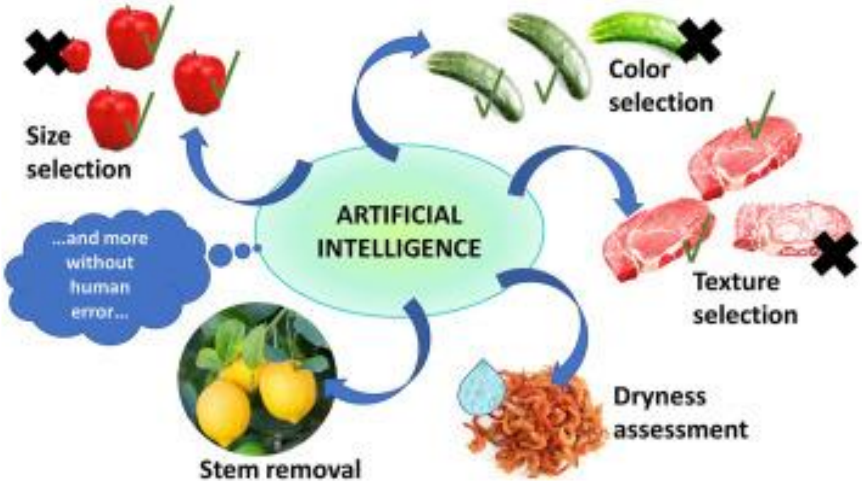

Figure 3. AI and Computer Vision based agriculture and food industry [9].

Image processing has been a relevant area of signal processing for a very long time. In simple terms, image processing is the use of mathematical operations to process signals as an image. This processing can be done either as analog or digital signals. The latter tends to be more common today due to the architectures commonly used in modern-day computers. Image processing is found in various tasks such as pattern recognition, image classification, anomaly detection, image restoration or enhancement, object segmentation, and many more. With the advent of growth in ML and Deep Learning, image processing in recent times has gained much advancement. In a classification task, image processing is required to help remove noisy information from the image data to increase the classification algorithm's efficiency and save it from the trouble of learning and discriminating noise. Such a technique can go a long way in a Smart Agricultural setting because data collected on the field can either be processed in real-time or over time. Real-time data are always prone to noise due to constant environmental change that occurs naturally. Hence, image processing plays a huge role in the collective efficiency of a Smart Agricultural system that captures image data. Computer vision is a part of smart agriculture that has seen a significant rise in both successful applications and research interest in recent times. Some of the most popular areas of interest in agriculture for CV and image processing are pest control, weeding, yield prediction, plant species recognition, that are discussed in Table 1.

Table 1. Summary of different computer vision methods utilized for various application areas in agriculture.

Author & Year	Application Area	Target Scenario	Technique Used	Results Obtained
[14]	Pest Control	Aphid's detection in the wheat field	Histogram of Oriented Gradient (HOG) features and Support Vector Machine (SVM) and	Identification accuracy of 86.81% and an error rate of 8.91%
[15]	Plant Species Recognition	Identification of plant species	LeafNet Convolutional Neural Network (CNN)	The top-1 accuracy on Foliage, LeafSnap, and Flavia is 95.8%, 86.3%, and 97.9%

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Table 1. (continued)

[16]	Weeding	Developed a machine to perform weeding naturally	Image processing operations like Hue, Saturation, Value (HSV), color conversion, and morphology operator procedures.	Average weeding rate of 90%, and the normal wet distribution space of surface soil is kept up with at 75%.
[17]	Plant Species Recognition	Recognition of plant species	Multilayer Perceptron with Adaboosting and feature extraction is done using morphological features	The achieved precision rate is 95.42%
[18]	Yield Prediction	Prediction of potato tuber yield	Elastic Net (EN), Linear Regression (LR), Support Vector Regression (SVR), and K-Nearest Neighbor (KNN)	The Root Mean Square Error (RMSE) for the four datasets (PE-2017, NB-2017, PE-2018, NB-2018) is 6.60, 5.97, 6.17, and 4.62 tons/hectare.
[19]	Pest Control	Pest control in coffee fields	Morphological operations and contour searching to identify the beetle and IoT based smart system to trap the beetle	The desired accuracy of the system was achieved
[20]	Yield Prediction	Cotton yield prediction in the field	K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest (RF)	The crop yield prediction accuracy using SVM is 72.8643%, KNN is 80.9045%, and RF is 95.8543%
[21]	Pest Control	Detection of Helicoverpa zea maize injury and tracking of lepidopteran pests in maize fields	Masked phone estimate and masked rotation estimate image processing techniques	The injury estimation is 95%

2.2. Internet of Things and Cloud for Agricultural Automation

Internet of Things (IoT) is another budding technology that has swept the industry and research in recent times. According to [22] by 2020, 20 billion devices will be connected to the internet. IoT technology connects and manages data from intelligent agents via an extensive network, primarily the internet [23]. Intelligent agents are referred to any electronic device that has its computing capability. Several areas in both research and industrial application like in healthcare [24], smart homes [25], supply chain [26], and many more have benefitted from this technology. Agriculture is another field that has vastly integrated IoT devices for monitoring/ surveillance, controlling, and managing agricultural processes. Gathering data on the field as it is being generated, processing them, and providing decisions in real-time (using Machine or Deep learning technology) can save a lot of effort and resources and increase overall production efficiency. IoT devices can provide live feeds of video surveillance to monitor livestock animals or even crops on the field for effective decisions. IoT technology has increased the interest of researchers and industry experts of Agriculture in Precision Farming, Smart Irrigation, and Smart Greenhouse. Cambra et al. [27] proposed an irrigation monitoring and controlling system, they read real-time data on the field and processed them on a cloud, and a mobile application to monitor and give control commands remotely. In Table 2, the authors discussed the summary of the recent researches in agricultural automation using IoT and cloud-based techniques.

Table 2. Summary of different IoT and cloud-based techniques utilized for agricultural automation.

Author & Year	**Target Scenario**	**Technique Used**	**Results Obtained**
[28]	Automated irrigation	Thermal imaging and Cloud of Things (CoT)	A thermal image with both low- and high-temperature values for the Irrigation Temperature Distribution Measurement (ITDM) results in a better irrigation system.
[29]	Sustainable and smart agriculture	Smart drone using IoT and Cloud Computing technology	Utilization of IoT provides the cutting-edge technology in agriculture and farming for high-quality crop manufacture and benefits of public cloud in agriculture are discussed to boost sharing of resources and data storage in cost effective way.
[30]	Analysis of soil quality and the movement of animals.	Arduino, Breadboard, and sensors	This low-cost model might help farmers in utilizing lesser amount of water to grow a crop, as well as in amplifying the yields and the quality of the crops by better management of soil during crucial stages of the growth of the plant.

2.3. Robotics for Agricultural Automation

Robotics is the technology utilized to design, construction, operation, and use of robots. A robot is a multifunctional machine programmed by a computer to carry out complex tasks in a simple and efficient way without human intervention. Robots are employed to reduce human ergonomics in various applications such as doing daily household work [31], space exploration [32], underwater exploration [33], healthcare workers replacement in covid-19 situations [34], etc. A greater amount of research has been done in the field of robotics. The extensive developments in robotics in recent years have given immense scope in the field of agricultural automation. There are various tasks in the agriculture domain that requires huge manpower and are also time-consuming such as irrigation, sowing of seeds, adding manure and fertilizers, monitoring of crops, etc. In order to automate and accomplish all these tasks in an efficient manner, researchers have developed electronic machines (i.e., robots) [35-36]. The summary of the recent researches in the field of robotics for agricultural automation is discussed in Table 3.

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Table 3. Summary of different robotics-based techniques utilized for agricultural automation.

Author &Year	Target Scenario	Technique/ Hardware Used	Results Obtained
[37]	Detection and recognition of ripe and unripe strawberries	Mask Recurrent Convolutional Neural Network (R-CNN) is used for strawberry detection	The average detection accuracy rate of ripe strawberry is 90% and unripe strawberry is 72%
[38]	Weed detection, drip irrigation, weed elimination for the wheat field	Convolutional Neural Network (CNN), 12V DC motor, NEMA 17 stepper motor, pH sensor	The precision, recall, and accuracy for weed detection is 94.7%, 92.3%, and 92.4%, respectively
[39]	Seed sowing	IoT module, seed discharger unit, ultrasonic sensors	Achieved seedling rates for different seeds such as 10 sec/2ft for groundnut, 8 sec/2ft for corn seeds, 15 sec/2ft for red gram dal, 36 sec/2ft for sesame seeds, 26 sec/2ft for almond

3. Discussion

There are various challenges also in the discussed technologies for the automation of smart and sustainable agriculture. If technology is a blessing, then it is also a curse. The use of technology makes our life easier, but it also has many disadvantages. The research gaps in smart agriculture can be broadly categorized into technical issues, business issues, and human issues.

3.1. Technical Issues

• Implementation Issues: Deployment of any automated application requires various resources like a good quality camera for image capturing, high processor, and memory for fast execution in computer vision-based applications. While for IoT-based applications, using unlicensed spectrum requires high-speed Wi-fi, semiconductor devices, cloud storage facility, etc. Thus, the aforementioned technical issues play a vital role in the implementation of smart agriculture applications.
• Reliability: If the proper implementation of the application is not done, it further leads to reliability issues. Since the whole agriculture system depends upon a device/application, it has to be reliable!! Also generally, agriculture devices are used outdoors and are thus exposed to harsh environments. This may lead to the degradation of the device and its parts like sensors, lens, etc. Thus, the physical security of the devices must be ensured as a priority.
• Collection of Data: Any AI-based model needs data to be trained upon. More the data used for training more accurate is the model. Thus, data collection is a very important issue to develop an AI-based model. Since the devices are still not very common to the farmers, collection of data is still a very challenging task and needs attention.

3.2. Business Issues

The cost of producing smart devices for agriculture is quite high as compared to the profit earned in that sector. Thus, there is always a trade-off between deployment and profit in this sector. The main issues related to the business are:

• Cost: The cost of deploying any application/ IoT device includes many factors. Set up cost that includes hardware, work station, gateways, Staff, etc. Running cost includes the purchase of the subscription, data collection, cloud service, maintenance, etc. Thus, it is a costly affair to develop application/ IoT devices for agriculture.

• Knowledge Required: Farmers especially in the rural areas lack the knowledge of using smart agriculture devices. Thus, they need to be properly trained so as to encourage them to shift from traditional agriculture methods to smart ones. There are many other challenges like competitive business, clients target, meet demand and supply chain, etc.

3.3. Human Issues

It is tough to change people's mindsets, especially those who have practiced using something for very long. This is the case with the farmers. Most of the farmers reside in rural areas and have been accustomed to using traditional methods of farming. It is a very challenging task to convince them to use smart devices/ applications for farming. Some of the major issues in convincing them are:

• Traditional Beliefs: The farmers have their own traditional beliefs in growing crops and harvesting them. Instead of relating it with scientific reasons, they go with their traditional beliefs.

• Awareness: Farmers are not properly aware of the smart devices available; thus, they feel hesitant to use them and prefer to go with the traditional farming methods.

• Availability: Since the agriculture regions are generally in rural areas, making the devices available to them is challenging. Also, the devices need a variety of interfaces that may not be available in rural areas. Thus, we need to first focus on the development of rural areas then make these devices available. Thus, we see that there are so many challenges to deal with to make smart agriculture more popular, and farmers may gain more and more from it.

4. Conclusion and Future Perspective

By 2050, the world population is anticipated to be nine billion as stated by the United Nations Organization, with almost 2 billion more people than today, leading to increase in demand of high quality and cost-effective agricultural commodities. The question that arises is how the current technologies will be able to fulfil the demands of increased population. Even the contraction of arable land region and its transformation to urban landscape can be considered as one of the reasons for the need of innovative advancements in meeting the agricultural commodities requests. In this paper, it can evidently be seen how innovations in computer vision and image processing algorithms have been utilized as smart agriculture practices to deal with pest control, weeding, yield production and plant species recognition. This survey gives further bits of knowledge into the most recent discoveries for smart agriculture developed with current technologies like IoT, Cloud and Robotics, to expand agriculture to sustain future prospects. A lot can be done in the area of Precision farming, Smart Irrigation, Smart Greenhouse, Livestock Monitoring and other applications through the integration of various technologies like IoT, Cloud Computing, Big Data Analytics, Image Processing, Robotics, Computer Vision, Deep Learning, Security, Blockchain, Virtual Reality and Augmented Reality. In addition, other cutting-edge innovations, like Unmanned Aerial Vehicles, remote and ground sensors, smartphones, drones, RFID tags and readers might also be utilized for smart and sustainable agriculture.

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