Review article

Artificial Intelligence in Smart Agriculture: Applications and Challenges

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Abstract

Keywords

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Artificial intelligence has been categorized as a subfield of computer science wherein machines perform smart learning tasks with the help of data and statical methods. Agriculture is one of the oldest social activities performed by humans. It provides many crucial things like raw materials, food, and employment. Due to the increasing population, it is the need of the hour that the agriculture sector should increase production of resources to match actual demand. Many agronomic factors such as weeds, pests, water condition and availability, and climate conditions impact overall yield. At present, methods used by farmers for management are traditional and insufficient to meet increased demand. To match future demand, new innovative agriculture methos need to be adopted. Artificial intelligence techniques in smart farm monitoring can enhance the quality and quantity of yield. This paper surveys different areas in agriculture where artificial intelligence is applicable. Artificial intelligence enables farmers to access farm-related data and analytical methods that will foster better agronomy, reduce waste, and improve efficiencies with minimum environmental impact. Various artificial intelligence techniques that make agriculture smarter than its previous forms are discussed. In this paper, the implementation of various artificial intelligence techniques in smart agriculture is studied. The aim of this study is to present different key applications and associated challenges to open up new future opportunities.

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1. Introduction

Over the last few decades, the human population has rapidly increased and demand for food has also increased rapidly. Agriculture is one of the oldest social activities of humans, and it plays an essential role in human survival. For various basic needs (food, oils, and clothes), humans depend on agriculture. Therefore, the survival of the human species without agriculture is very problematic [1]. To meet future demand, an increase in crop production by 100% over the period 2005 to 2050 is necessary [2]. Furthermore, to satisfy future food needs, a global-scale effort will be necessary and a range of global factors such as global-level farming, diet changes, and reduction in food wastage are required to be implemented [3]. The use of available croplands in innovative ways may contribute to achieving the desired demand [4]. Moreover, it required a thorough assessment to facilitate delivery of future demand for crops. However, the use of traditional methods of cultivation by farmers can affect crop degradation. In addition, inadequate knowledge of soil fertility, water management, pest management, and so on can also lead to crop degradation [5]. Farmers directly use pesticides in a hit-and-trial method that leads to unhealthy or less production. It is very difficult for farmers to get full yields. Many agronomic factors such as climate changes, pests, weeds, and diseases affect the yield capacity of crops worldwide. Artificial intelligence (AI) has been adopted by many sectors as a transformational technology in this digital age. It is an emerging and advanced field of computer science that has actively contributed to the field of agriculture. Compared with traditional agriculture methods that heavily require precision and depend on human labor, AI provides a more accurate, efficient, and safer way to perform any task without any direct human intervention. Recently, many advanced methods have been applied to agriculture including computer vision [6, 7], internet of things (IoT) [8], intelligent systems [9], machine learning [10], robotics and so on. These have helped farmers to analyze land suitability [11], water management [12], and describe the best crops for a specific region to get maximum yield. The increasing interest and efforts of researchers in the field of agriculture help to improve the quantity as well as the quality of agricultural products.

Pesticides and other chemicals are sprayed over farms to improve overall production. AI as a part of a smart farming management system can also be used by the farmers to improve the way in which the pesticides are applied based on place, time, and safety considerations. It can also help to detect and classify the accurate features of crops to improve the quality of food and reduce waste. Machines empowered by AI can use data to reveal hidden traits that significantly contribute to crop quality. Water management in agriculture with AI application can be used to estimate evapotranspiration on a daily, monthly, or needs basis. It allows irrigation to be used more accurately and effectively [13]. Furthermore, AI can facilitate better measurement and the prediction of daily dew point temperatures which can aid in the recognition of expected weather patterns as well as in the forecasting of evapotranspiration. Farmers increasingly used AI models that include sensors and robots to monitor crop condition and collect related data. The collected data helps the farmers to better understand their crops, potential crop diseases, and the genetic basis of their farming.

Previous researchers examined AI in agriculture and a range of issues concerning its use in agriculture emerged. Articles related to the use of AI in agriculture focused on specific subjects such as wireless sensor networks (WSN), IoT, machine learning, big data, supply chain, and farm management system. However, to the best of our knowledge, reviews that were focused on the applications as well as technological challenges associated with AI and smart agriculture were rare. There are many challenges to be faced when applying AI in agriculture. For example, spatial data can directly affect decision-making, data processing, and precision machinery employed to address variability in crops [14]. The use of devices and sensors on vehicles in farming systems, on machinery can also be required to operate fleets of vehicles in a coordinated fashion. The communication between the sensors and vehicles creates issues related to the network infrastructure

[15], uncertainty in environmental conditions, and weather changes. These limitations obligate the AI system to handle infrequent data and increase the complexity of processing as well as the decisions making. These issues can be addressed by focusing attention on the general application areas and identifying the related challenges. The aim of this study is to provide an in-depth discussion related to the adoption of artificial intelligence in agriculture. In more details, the objectives are:

- To describe current trends involving the use of AI in smart agriculture, the latest technologies, the generation of data, the processing of data, and the path from traditional to smart agriculture.
- To investigate different applications of AI in agriculture.
- To investigate the challenges encountered when applying AI technology in smart agriculture.

The structure of the study is divided into different sections. Section 2 is divided into subsections that discussed: AI in agriculture and the adoption of the smart farming system. Section 3 describes different application areas of agriculture that employ AI for better production. Section 4 discusses the challenges related to AI technologies. Section 5 gives a broad discussion of the study and provides related solutions. Finally, Section 6 concludes the study and suggestions of future directions for research and development.

2. Traditional Agriculture to Smart Agriculture

2.1 Timeline of the agriculture revolution

Agriculture plays a vital role in economic and social stability. The agricultural revolution based on productivity improvement and restriction of the era is depicted in Figure 1. The Figure can help readers to understand the past revolutions from Agriculture 1.0 to Agriculture 4.0 [16] and confront the related issues.

- Agriculture 1.0: refers to traditional agriculture practices between 1784 and 1870. The period featured the use of indigenous tools and animals for farming. Such types of farming required very high labor resources.
- Agriculture 2.0: refers to agriculture revolution 2.0, a period that saw the start and development of the mechanized world. Gas and oil replaced steam energy sources and contributed to different farm activities as well as to a much larger and complex supply chain. In the 20th century, the concept of assembly lines for mass production were introduced to improve efficiency in agriculture. But, low utilization of resources was always a big issue.
- Agriculture 3.0: refers to the revolutionary era between 1992 to 2017. It enables communication and software engineering technologies in agriculture to introduce automation capabilities. The aim of this concept was to explore information technology and make precision agriculture more sustainable. But, the level of intelligence was always considered in this revolution.
- Agriculture 4.0: refers to the era that began in 2017 and is ongoing. This latest revolution has seen the development and combination of different advanced technologies such as WSN, IoT, AI, big data, and blockchain and their application in agriculture to transform it in ever smarter ways [17]. The revolution has enabled intelligent agriculture systems with real-time decision-making capability. Real-time farm management systems used high automation and data-driven approaches to ensure better production, supply chain management, and food security. However, security challenges remain one of the main bottlenecks in this development.

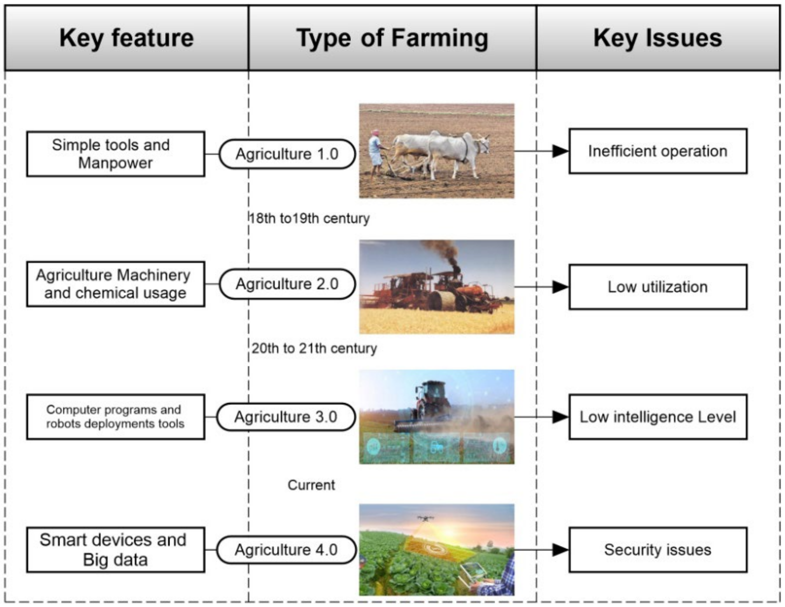

Figure 1. Agriculture 1.0 to Agriculture 4.0

Smart agriculture that has developed in revolution 4.0 can be divided into three development modes [18]: 1) Precision agriculture, 2) Facility agriculture, and 3) Order agriculture. By embracing smart agriculture, farmers can make more informed decisions, optimize resource utilization, reduce costs, and increase yields. Furthermore, it can help to address some of the challenges facing the agriculture industry, such as climate change, water scarcity, and food security.

2.2 Process of artificial intelligence in smart agriculture system

Farm management systems use field data to perform smart decision-making tasks. Data acquisition from farms is collected with the help of IoT sensors, remote sensing, and other historical records. These data can be related to soil, diseases, pests, previous yields, weather, or come from IoT-based sensors. The collected data is stored on local and cloud-based storage systems and is used with some specific types of algorithms to train models. These processes are executed repeatedly during the harvesting period. It will help to maintain farms with the least detrimental effects and maximize overall production [19]. The process of an AI-based smart agriculture system is shown in Figure 2.

In the last step, the processed information is used by the decision system to execute advanced machinery commands or make recommendations. The model provides useful information and allows the processing of real-time data. The different components of the smart agriculture system are discussed below.

2.2.1 Data dealing

The data dealing phase in smart agriculture involves data acquisition and storage. Data acquisition is performed with the help of internal and external devices including sensors and actuators, network resources, and past data storage devices to obtain the information. Sensors sense the environment

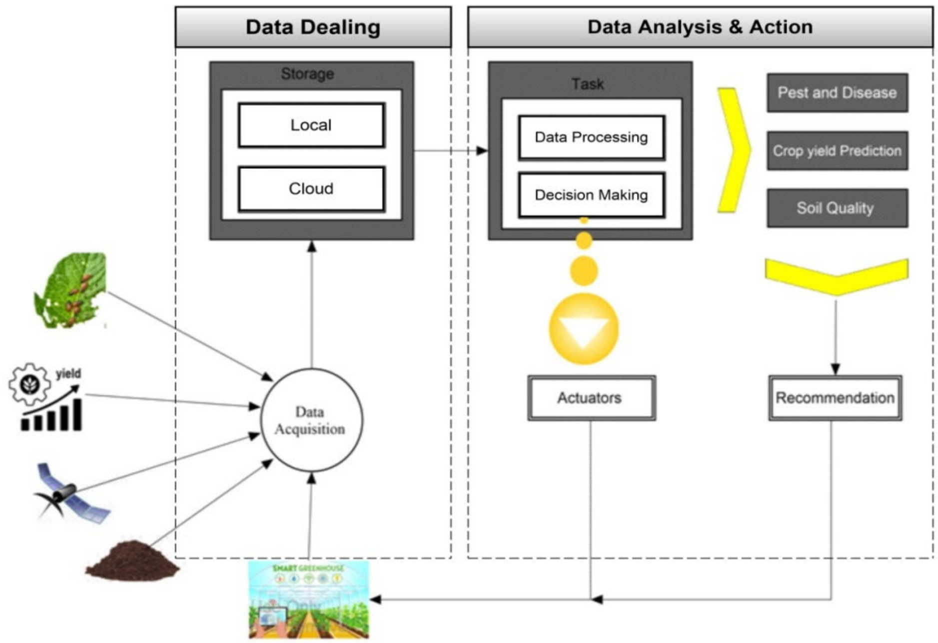

Figure 2. Smart agriculture system

and transmit the corresponding values to storage devices. Various types of sensors used by the system are classified by their functionalities: location sensors are used for getting information about the crop location, electrochemical sensors are used to detect chemical reactions in soil, light dependent resistors (LDR sensors) are used to detect the condition of light, and nanostructured sensors are used to analyze humidity in the soil [20]. Sensors collect information related to the soil, plant ecosystem, location, and so on. Satellites generate data with the help of remote sensing technology that is used to monitor ecological conditions, estimate area, and monitor growth. Apart from these, past data related to various factors including crop yield, weather conditions, evapotranspiration, and so on, are applied in smart agriculture for getting useful insights.

Data transmitted from the different sources are saved for future use in a secure environment. The storage environment may be local or cloud-based. In local storage, the devices are directly connected to the system without any centralized management [18]. In such an arrangement, only the host system has the privilege to access the data. In contrast, cloud-based storage is generally a network-based storage system used for data storage in a distributed environment. It provides scalability to access the data smoothly.

2.2.2 Data analysis and action

The volume of agricultural data has undergone an explosive increase in recent years. AI can be used to analyze data, extract hidden information, and increase final productivity. Data analysis is generally related to the extraction of useful features and provides insights into the data using appropriate methods. The insights that can flow from data analysis are essential for informed decision and recommendation making. Data analysis and related action generally include autonomous robotics, monitoring systems, and predictive analysis [18]. Agriculture robots are embedded systems that integrate multiple technologies such as computer vision, robotics, AI, etc.

Robots are widely used by modern industries to boost overall production and increase reliability in repetitive tasks. They have the potential to deal with seed sowing, spraying, and harvesting. For example, a smart weeder system can easily differentiate weed samples from the crops with the help of computer vision, and it can then handle the weeds without any crop loss [21]. Picking robots in farms use computer vision techniques to efficiently classify the fruits and vegetables that are ready for harvest. After that, they determine the location of the produce to be harvested and collect it in the box. For the monitoring systems, some specific sensors are used by the system to continuously monitor farms. Sensors take the values from the farms and send them into a processing unit for analysis. The processing unit analyzes the data and produces some decision-making outputs. After that actions and recommendations are produced by the system for targeted output. In predictive analysis, machine learning models are used to predict the yield of the crop, and forecast the impact on farming of weather changes, and other factors.

3. Technologies for Exploring Smart Agriculture

AI has the potential to be embedded in agriculture enterprises and make them smarter. Advancements in these technologies will replace repetitive tasks and help farmers to produce the most appropriate output and improve the quality of production [22]. Figure 3 shows different technologies associated with smart agriculture practices such as machine learning, deep learning, WSN, robotics, etc. These highlighted practices further support the evolving field within smart agriculture, providing novel research and development edges, creating potential for business growth.

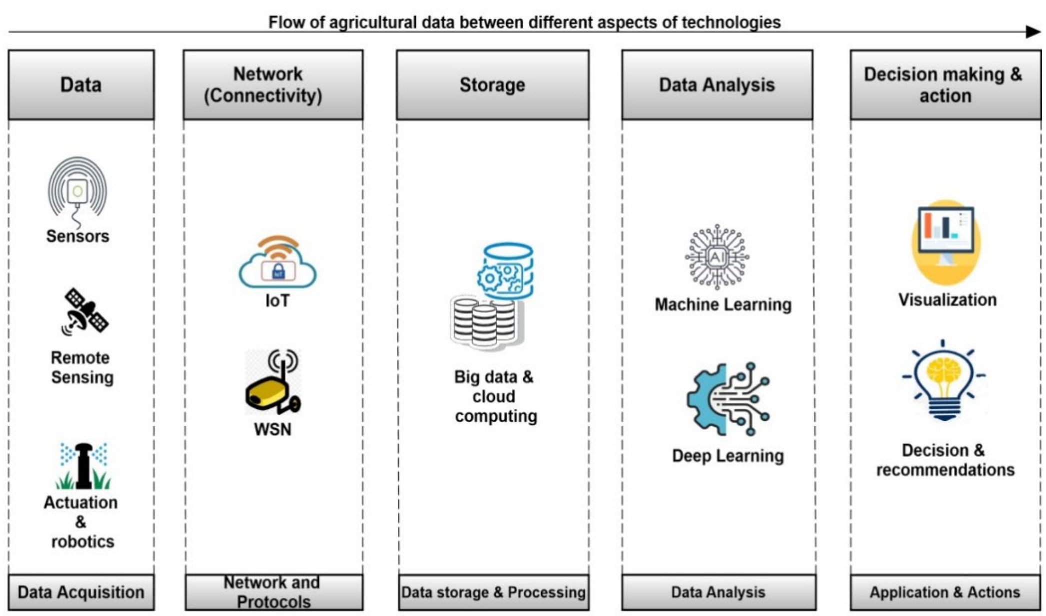

Figure 3. Core technologies in smart agriculture

These technologies can revolutionize agriculture and help to modernize the processes. Data related to farm sensors, remote sensing, and unmanned aerial surveys helps farmers to gather the information, visualize it and predict the health of crops. They provide cost-effective warning systems that can recognize the related issues and give solutions at the early stage. AI algorithms such as machine learning help to perform different tasks like regression analysis, classification, and association analysis to illustrate the relationship between dependent and independent variables. Deep learning models transform data from one dimension to another dimension through different levels of abstraction. They use several layers hierarchically to extract the features from the data automatically and transform these features into meaningful features to make accurate predictions [23]. Digital image processing supports a wide range of image formats produced by digital cameras, satellites, sensors, and medical imaging instruments. These AI algorithms can generate useful actionable insights that help to increase yield, control diseases, and pests, and reduce farmer workload. Thus, this section gives a broad overview of the roles of different technical aspects that were identified previously and used with smart agriculture.

3.1 Sensors and robotics

Sensors are the smallest units underlining the concept of smart farm management. Continuous advancements in technology have made them less expensive and smarter at sensing the surrounding environment. Over the past few decades, both wireless and wired sensors have been widely utilized in the farming sector [24]. In agriculture production, temporal and spatial variability which is important can be managed with the help of two approaches: a sensor-based approach and a map-based one. To ensure environmental sustainability with improved crop production, both approaches involve mobile or stationary sensors that produce massive data required for efficient farm management. Sensors are already successfully being applied in the different areas of smart agriculture such as soil monitoring [25], irrigation, weed control [26], and disease control [27, 28].

Remote sensing in agriculture is one of the generic ways to collect data from a distance and measured by specific instruments without any physical contact [29]. Remote sensing uses small ranges of the electromagnetic spectrum (microwave, visible and reflective infrared waves) to produce remote sensing data. Remote sensing is being widely used to assess vegetation health by measuring environmental stress and growth. Additionally, AI-embedded remote sensing has been used for addressing crop nutrients, crop yield, water stress, soil properties, and crop diseases [30].

In recent years, robots with actuators and sensors have been increasingly utilized in agriculture practices such as irrigation, target spraying, monitoring of weeds, soil management [31], pest management, and harvesting. Mobile robots rather than fixed robots may offer larger benefits in the context of agriculture practices. They can cover a wide range of areas with the help of remote sensing to differentiate the various types of landscape conditions. Such systems, which can automatically navigate different terrains, have improved many current agricultural practices. In this regard, the unmanned group vehicle (UGV) and unmanned ariel vehicle (UAV) have great potential to deal with different agricultural applications such as crop pest detection, disease detection, crop yield estimation, weed detection, and irrigation control [32]. These robotics practices can increase efficiency and greatly reduce the need for human labor.

3.2 IoT and WSN

The internet of things (IoT) is used in several areas such as smart cities, smart vehicles, and smart agriculture and industry. The target of IoT is to integrate the virtual world with the physical world. It uses the internet as a communication medium and exchanges information between platforms. A typical IoT ecosystem generally includes network and communication devices to produce reliable output and deliver data related to user services. Based on different protocols, IoT architecture can be divided into a three-layer (top, bottom, and middle) structure. The top layer is generally considered to include user functionalities. This layer manages the entire IoT system. The bottom layer is known as perception or sensor layer. This layer is responsible for acquisition of data through sensors. The middle layer is related to the network infrastructure. It is responsible for routing and transmission of data. Nowadays, IoT has become a core technology, and it in turn stimulated transformations of agriculture [33]. In agriculture, IoT is used for livestock monitoring, precision farming, weather tracking, system controlling, soil management, weed management, pest management, supply chain management, and so on [34, 35]. It improves the acquisition of data and minimizes human intervention. Data collected by smart devices (robotics, sensors, etc.) are transferred utilizing a wireless or wired network to the server.

In recent years, wireless sensor networks (WSNs) have been widely used to improve traditional farming methods for various agricultural practices. Sensor-associated networks perform sensing, communication, and computation using hardware nodes and software. They use various types of sensors to monitor air quality, temperature, humidity, pressure, etc. Continuous development of WSN infrastructure has made it applicable in several agricultural areas such as crop monitoring, irrigation system, weed monitoring, disease monitoring, agricultural machinery, etc. Previous researchers described an advanced variant of a WSN connected with an actuator such as valve, pump, or sprinkles and interacts with the environment to perform real-world tasks [36]. WSNs helps to utilize the different applications in smart agriculture to improve and optimize agricultural practices [37]. Consequently, they have contributed to improving efficiency, profitability, and sustainability in agricultural production, and also help to mitigate wastage, reducing the adverse impacts on the environment.

3.3 Cloud computing and big data

Cloud computing is an internet-based infrastructure that provides the services of software, storage, infrastructure, and platforms through wireless communication. In recent years, cloud computing has become a popular technology that provides data storage for agricultural applications and helps to reduce storage costs. It also provides a safe and large-scale computing platform to transform raw data into useful information that farmers can use to make the right technical decisions. In agriculture, cloud computing provides web-based storage space that can be used for farm management [38]. It assists farmers to improve agricultural practices and provides interconnections between external and internal services to create a sophisticated and advanced marketplace. Despite the advantages of cloud computing, it also has limitations. A large volume of data generated by different applications in a short amount of time is very sensitive with low latency of network [39]. This situation sometimes makes data computing unfeasible because these applications are required to exchange constant information with the cloud. To overcome the limitation of computing unfeasibility, the concepts of fog and edge computing were introduced by researchers. These allow computing services to perform at the edges and middle layers of the network. These virtual layers typically facilitate real-time analytics as well as providing data aggregation between different sources and data fusion for further processing. The adoption of IoT and WSN technologies in agriculture has facilitated data collection at every stage. They generate large volumes of data but the exploitation of the generated data in the agricultural sector is relatively low [40]. Opportunity for data-driven approaches concerning agricultural optimization have been neglected. In fact, big data analytics can play a vital role in transforming, processing, and visualizing complex agricultural datasets into informative formats [41]. The big data concept generally follows the 5v dimensional model of velocity, volume, value, veracity, and variety. Recent research has shown that big data has considerable impact on smart agriculture. In agriculture, big data analytics helps to find the optimal parameters such as temperature, rainfall, and seed breed, and this has involved the creation of a huge historical dataset that has proven to be valuable in crop yield improvement [42].

3.4 Machine learning and deep learning

With advancements in data acquisition, IoT, WSN, and cloud computing technologies, the amount of data in agriculture has increased dramatically. Artificial intelligence applied for analysis with machine learning and deep learning has become one of the main pillars of smart agriculture [43]. In machine learning and deep learning, tasks are generally categorized into supervised, unsupervised, and reinforcement learning. In machine learning, learning tasks are performed with the help of data and targeted to minimize the error rate with the help of some specific models. Recent studies highlighted that these technologies are promising in agricultural data analysis [44]. The exploration of these technologies in agriculture was illustrated by different applications such as weed detection, soil management, crop monitoring, and irrigation management [45]. The algorithms analyze the data for the identification of hidden trends, relationships, and complex patterns that help to maximize crop production as well as minimize input costs [46]. They also provide an accurate prediction that helps to improve operational management and decision-making in agricultural practices. Machine learning algorithms in the context of smart agriculture data analysis include random forest (RF), deep neural networks, support vector machine (SVM), and so on. These algorithms used with new generation software can facilitate real-time insights and recommendations for proper decision-making in agriculture [47].

3.5 Decision-making systems

Decision-making system typically involves an analytical mechanism that provides quick and easy decision-making capability from complex data. This process uses raw data as well as analytical tools to convert the output into knowledge and is demonstrated through a user interface. To process complex data for proper agricultural management, decision support system (DSS) can offer an indispensable approach. They help farmers and stakeholders to make a proper decision based on complex and poorly defined data. It is a very tedious task for the stakeholders and farmers to encounter proper decisions after the transfer of an explosive amount of data into knowledge [48]. In this, DSS can assist with the making of precise decisions that are based on evidence. In the last few decades, agriculture decision support systems (ADSSs) such as AgriSupport II [49] and Multi-robot sense-act-system [50] were proposed by the researcher to provide sufficient decision-making suggestions to the farmers. The AgriSupport-II features a farm planning algorithm, which creates farm plans based on attributes such as mode (which defines the best possible plan for agriculture), technical path (which defines the sequence of operations), resources (which defines required resources such as labor and machinery used to estimate the cost of operation), precedence (which defines the priority of operations), and time window (which defines the time from the start to the completion of operation). After taking this input, the farm planning algorithm calculates the cost of all modes and compares it with the best one. In an experimental study, the AgriSupport-II system was utilized on twenty-five different crop combinations in Spain where it provided sufficiently advice about agricultural work. The system had some limitations in that it required manual attributes to categorize the most relevant suggestions. In this regard, an autonomous multi-robot sense act system was developed by the researchers. The proposed system used ground or aerial vehicles to maintain crop performance. The system was able to suggest farming tasks and provided strong decision support for farmers. However, it had some limitations such as valve delay and internal vehicle error.

4. Application of Smart Agriculture

An in-depth survey of different application domains of smart agriculture such as various opportunities and innovations brought by smart agriculture are discussed. Smart agriculture has the potential to make revolutionary changes in the traditional farming process. Farming is a stepwise process, as shown in Figure 4. The steps occur in sequence with specific time intervals.

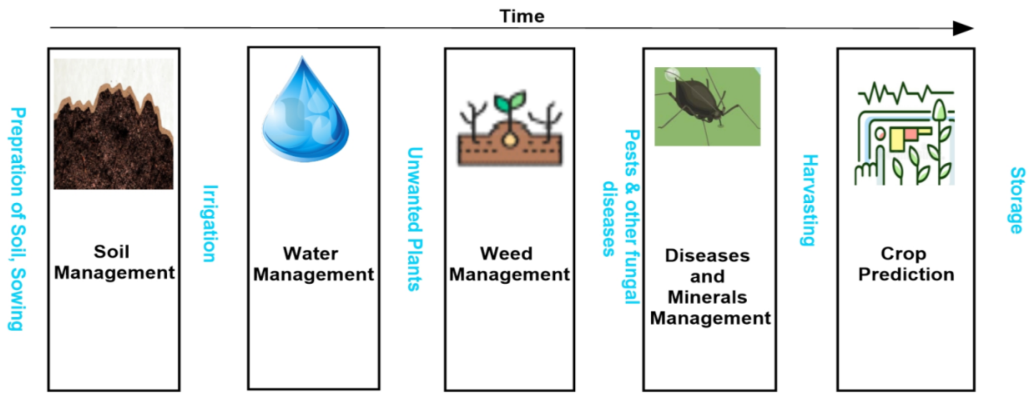

Figure 4. Different application domains of smart agriculture

4.1 Soil management

Soil in agriculture plays a very important role because the yielding capacity of a crop is directly related to soil quality. If the quality of soil is not at the desired scale, it becomes a bottleneck in plant growth. Many discoveries have already been made for regular assessment of soil quality. AI can be used to investigate soil nutrient deficits and potential flaws. AI-based applications can be used to analyze the growth of flora patterns in agriculture and support farmers' understanding of different nutrient values and soil imperfections. Zhang *et al*. [51] developed a real-time IoT-based moisture and nutrient monitoring system for a citrus crop. The system was divided into four different layers: the perception layer (responsible for data acquisition), the transmission layer (responsible for data transmission), the information layer (provides information from the data), and the application layer. The proposed model expanded the detection range and improved model accuracy. Chen *et al*. [52] conducted a study on soil management. They showed how SVM, decision tree (DT), and artificial neural network (ANN) techniques could be adopted in this context. These techniques help to adjust soil parameters leading to positive agricultural growth. But some barriers related to the data analysis were discussed by the authors. They were the main bottlenecks for agricultural system improvement.

4.2 Water management

The agriculture sector is a water-demanding sector. Therefore, it is crucial that water wastage from farming be minimized [53]. Modern technologies embedded with agriculture make farming smarter compared to previous approaches. Many techniques like expert systems, embedded systems, IoT-based systems, and other approaches have assisted in the advancement of irrigation systems. Aggarwal and Kumar [54] proposed a system that collects data related to soil moisture, humidity, pH level, and temperature with the help of some specific sensors. After that, the collected data is analyzed by the ANN to generate results of high accuracy. The system triggers and controls the flow of water at the required portion of the farm after getting the relevant result. Mohanraj *et al*. [55] used WSNs to automate an irrigation system. The model included monitoring of real-time weather conditions and soil, and helped farmers reduce the overall cost of irrigation and improve their methods of farming in an intelligent way. The proposed system successfully worked for both surface and sub-surface drip irrigation.

4.3 Weed management

Weeds are undesirable plants that grow in a specific situation automatically. They are one of the most severe biological constraints on agricultural systems as they compete for water, light, and other nutrients that affect a plant's microclimate [56]. In addition, weeds become a reason for overall yield degradation in crops. Traditionally, it required lots of effort and resources to control weeds in farming. However, advancements in knowledge and technology have changed the working scenario in several ways. AI use in weed management helps farmers to handle weed management faster and at a bigger level with minimum resources. In this regard, Alam *et al*. [57] proposed a real-time vision-based sprayer. This model used 396 images of weeds and crops. In this image dataset, 99 images were used for model training. After training, the system was deployed in a real environment for performing weed detection tasks and calculating plant pixel area. The processed results were shared with the microcontroller which then controlled the on/off switch of the sprayer, achieving 95% prediction accuracy. Brilhador *et al*. [23] proposed a model with the help of a deep neural network for real-time weed detection. The proposed model achieved 83.44% prediction accuracy. The researchers also investigated the impact of data augmentation on the pixel-wise classification of weeds and crops. Tejeda and Castro [58] proposed a model that used image processing to successfully detect weeds in crops. The algorithm took images as input, detected green plants, and eliminated other parts. After that the algorithm removed irrelevant information with filters. Finally, labeling was done, and thresholding was used for weed detection. The algorithm was capable to classify weeds with good accuracy in a real-time environment and achieved 95% prediction accuracy.

4.4 Diseases and pest management

The spreading of crop diseases due to nutrient deficiency or pests is a factor that hampers the production and quality of food. Like other living species, plants require nutrients to survive. The signs of diseases and essential mineral deficiency appear on plant leaves. Identifying the cause of such problems can be difficult for farmers who may lack expertise. In this context, artificial intelligence can help to detect diseases and deficiency of nutrients in the early stages. It can help to prevent diseases in their early stages, suggest the exact quantity of pesticides [59], and control other factors that may be a cause of plant degradation. Singh [60] presented a low-cost, automated, and easy-to-use solution that allowed farmers to diagnose plant diseases accurately without a human expert being present. The proposed model used a cloud-based dataset for training. This model gave 95% detection accuracy of disease in 4 groups (bacteria, mildew, Phoma, and red rust). Bahtiar *et al*. [61] proposed a model with the help of region-based convolutional neural network (R-CNN) architecture for the detection of three kinds of mineral deficiency in chili plants. The author created a dataset of 270 images divided into four classes. The research was done in Boyalali, Indonesia. After training, the proposed model gave 82.61% detection accuracy.

4.5 Crop prediction

If the prediction of crop yield is accurate, it may help farmers to make important decisions regarding crop harvesting. It may give them an idea about the total damage due to climate change, help them decide what to grow and the best time to grow it, and assist them to obtain maximum production of crops [62]. Crop predictions can also assist interested parties to make crucial decisions concerning total required storage spaces, food shortage, pricing, and importing and exporting. Farmers and government need to follow a model which helps to predict the yields more accurately for making farming smarter and help farmers to predict total yield in a more accurate and fast way with minimum required resources. Prediction of crop yield depends on different factors and conditions such as climate, soil condition, varieties of seed, and fertilizer use [63]. Medar *et al*. [64] implemented a method for crop selection that helped farmers to get maximum yield. The proposed method predicted crop yield rate in three phases. In the first phase, the dataset was managed for the model. The second phase was the testing of the dataset, and the third step was related to analysis. In this study, the Naive Bayes algorithm gave the best prediction accuracy of 91.11%. Oikonomidis *et al*. [65] studied different deep-learning approaches for crop prediction. The authors observed that convolution neural network was the most common and best algorithm. In this study, root mean squared error (RMSE) was the best evaluation metric suggested by the authors. Other challenges were related to the unavailability of a large and accurate dataset, the need for better parameter tuning, and many other hurdles that would need to be overcome in future research.

4.6 Harvesting

Harvesting after the riping of crops is one of the most essential, time-consuming, laborious, and error-prone activities. The cycle of harvesting crops depends on the crop type. Some crops require a single cycle while others required several harvesting cycles even on a regular ripping basis or daily basis. This process requires the right time adoption because time is a critical factor in harvesting; either late or early harvesting can affect the overall yield production of crops. Additionally, it is a laborious and time-consuming process that requires a lot of resources. Considering these issues, agricultural experts have suggested that the involvement of robotics in agriculture may provide flexibility in harvesting. Over the last few decades, the harvesting process aided by robotic technology development has become more precise and automated. In this regard, researchers have improved methods of measuring the shape, color, and size of fruit, often using locally available facilities. Highly specialized tools were used to distinguish characteristics between targeted fruit. De-An *et al*. [66] developed a robot for apple harvesting in harsh environments. To make this task possible, different equipment such as an image manipulator module and an end-effector is used. The end-effector adopted a spoon-like shape with a pneumatic gripper for apple harvesting. The developed robot could perform the harvesting task autonomously with a success rate of 77% with 15 s of average harvesting time. Li *et al*. [67] developed a litchi harvesting robot with a camera and picking arm. The system used a 6-Degree of Freedom (DoF) liftable manipulator and Deep Lab V3 image segmentation. The final developed robot was finally tested on real crops, and it achieved an 83.33 % accuracy ratio.

4.7 Supply chain management

The agri-food business consists of multiple steps of transactions. Each step is followed by another step with different conditions. These steps with different functionalities collaborated into a supply chain. It generally includes food processing, transportation, food storage, and information about the distributors. These steps collectively require a large amount of data maintenance and management, which can be tedious to do manually. Therefore, smart technologies including smart contracts can assist the whole process of supply chain management. Awan *et al*. [68] proposed a framework that used front-end and base technologies for the smart manufacturing process. Front-end technologies are deals between manufacturing, smart products, supply chain management, and working process.

On the other hand, the base technologies are considered IoT and cloud services. The authors showed that in smart manufacturing, technologies play an important role. Xiong *et al*. [69] showed that blockchain technology can create a trustworthy relationship between consumers and producers. It is a data-driven approach and involves smart contracts. It allows the stakeholders to make timely payments that triggered into the database with the help of blockchain technology.

5. Technologies and Applications

A boom in artificial intelligence techniques makes it applicable in agriculture. Table 1 shows smart agriculture technologies arranged by domain with connected applications: SM, soil management; WDM, weed management; WM, water management; DPM, disease and pest management; CP, crop prediction; HR, harvesting; and SCM, supply chain management). AI technologies help farmers to make accurate or near-accurate predictions that help in decision-making. In irrigation, smart irrigation systems replace traditional methods, helping to minimize the consumption of water. In pest and disease management, smart image processing is used by farmers to make an accurate prediction of pests and diseases. It can help farmers to effectively apply pesticides and other chemicals.

6. Challenges in Smart Agriculture

Despite the numerous advantages of smart agriculture, there are also some limitations associated with the different domains of technologies used for the implementation of smart agriculture systems. In this context, it becomes necessary to address all these transitions toward this paradigm. This section provides different challenges associated with various domains of technologies used in smart agriculture systems, as shown in Figure 5.

6.1 Data level

The performance of smart agriculture systems heavily relies on data quality. It is a domain that requires different data sources to support ecological and economic decisions [32]. Therefore, standardization of data is the backbone of agricultural information management systems. In agriculture digitalization, the attributes of privacy, quality, and integrity of data are the main areas of concern that have been focused on by the researchers. In precision agriculture, a series of devices such as sensors, global positioning system (GPS), cameras, and remote-control systems are often used for data collection. In case of modification or malfunction, the collected data may lack integrity and quality [43]. This leads to big losses in the farm management systems and damage to crop production. To ensure the quality of data, it is categorized into intrinsic, contextual, representational, or accessibility. These traits have been described as crucial for unlocking the full scientific value of data resources and exploiting the capability of smart agriculture systems. Hence, future consideration can help to jointly enhance the dimensions of data quality that lead to the effectiveness, performance, and trustworthiness of smart agriculture systems.

Table 1. Smart agriculture as per domain and technologies, along with their associated applications

Domain	Technologies	Description and References	Application						
			SM	**WDM**	**WM**	**DPM**	**CP**	**HR**	**SCM**
Data	Sensors	• Sensors in smart agriculture are deployed to measure farm-related data for different purposes [24-28].	✓	✓	✓	✓		✓	
	Robotics	• Robotics such as UAV, UGV, and other integrated advanced systems in agriculture collect onsite data that helps to reflect useful information [31, 32, 57, 66, 67].	✓	✓	✓	✓		✓	
	Remote Sensing	• Remote sensing helps to evaluate the distributed parameters of farms to measure the different agriculture practices [29, 30, 62].	✓		✓	✓	✓		
Connectivity	IoT	• IoT system makes connectivity between different agricultural things and helps to manage farm-related tasks [33-35, 51, 54, 68].	✓	✓	✓	✓			✓
	WSN	• WSNs in agriculture have great potential to deal with precision fertilizers, disease management, and other tasks for farm management [36, 37, 55].	✓	✓	✓	✓			
Storage and Processing	Cloud Computing	• Cloud computing systems are deployed in agriculture to enhance real-time decision capabilities [40-42, 60].			✓	✓	✓		✓
	Big Data	• Big data integration in smart agriculture helps to optimize the strategies to achieve sustainability [38, 39].		✓		✓	✓		✓

Table 1. Smart agriculture as per domain and technologies, along with their associated applications (continued)

Domain	Technologies	Description and References	Application						
			SM	WDM	WM	DPM	CP	HR	SCM
Data Analysis	Machine Learning	• Machine learning provides high-precision algorithms for data analysis to make agriculture practices more effective and efficient [44, 45, 52, 64].	✓	✓	✓	✓	✓	✓	
	Deep Learning	• Deep learning is an innovative technology that provides a complex relationship between agricultural data [44, 46, 47, 57, 58, 61, 65, 67].	✓	✓	✓	✓	✓	✓	
Decision and recommendation	Decision Support System	• Decision support systems transfer data into explosive information to produce the best decisions and recommendations for the agriculture systems [48-50].	✓	✓	✓	✓			✓

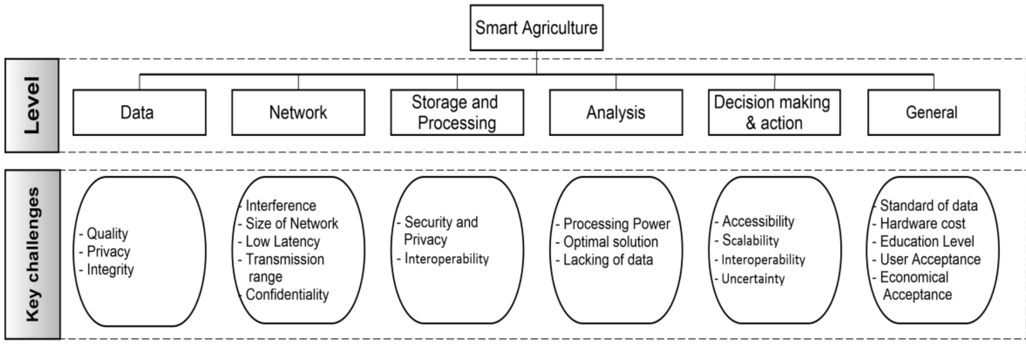

Figure 5. Levels of challenges in smart agriculture

6.2 Network layer

In smart agriculture, wireless connectivity covers a wide range of areas and provides various advantages such as flexibility, low cost, and high scalability. Connectivity between different devices such as communication devices or sensors enables data transmission at the network level. However, network size, interference, low latency of the network, and range of transmission affect the performance of devices [37].

In agricultural digitalization, the network layer is responsible for transmitting signals from low levels to upper levels. The transmission of a large amount of data from the perception level to computational units over a wide area makes threats to data confidentiality in the network layer [70]. Additionally, the size of the network or the number of connected devices for communication further needs to be optimized and focused. Other than these issues, the best optimized spatial distribution of nodes to be placed in a smart agriculture system needs to be considered.

Smart agriculture systems use different technologies for wireless communication such as Bluetooth, Zigbee, and Wi-Fi. In this regard, adverse environmental conditions, the size of the network, and same frequency devices may reduce the latency of the network. The interference due to low latency leads to abrupt disconnection in devices and poor performance [32]. Furthermore, transmission over long distance in smart agriculture also needs to be considered seriously when implementing network devices. If the distribution of devices is performed over a long distance, it requires high transmission ranges which demand high energy resources. Therefore, it is an essential task to choose an appropriate transmission range as well as protocols for efficient communication. In smart agriculture, a huge amount of data is continuously generated by the sensors. This generated data is collected and processed by the processing units. Furthermore, in smart agriculture systems, security and privacy require special attention [71]. The security threats that can affect smart agricultural systems demand solutions with better security mechanisms.

6.3 Storage and processing

Devices that provide satellite imagery and sensors used in agriculture generate data at every step. Satellite imagery has generally been used for crops and land monitoring over a large area. Thus, it is beneficial to the implementation of data-driven agriculture. However, it is a tedious task to integrate different forms of data that come from various sources such as farmlands or enterprises [72]. In fact, data interoperability contributes to improving the value of dispersed data after the data collection.

Apart from novel standards, security, and privacy have always been seen as limitations for cloud computing in the agriculture industry. Furthermore, shifting between the different cloud service providers and fulfilling the security standards have also been conceived as the additional limitation of cloud implementation for smart agriculture [40].

6.4 Data analysis

Deep learning and machine learning in AI are one of the most suitable technologies used for data analysis. In agriculture, several problems have been tackled with the support of these technologies. However, high innovation and advancement always arise with some limitations [40]. One of the major challenges faced by machine learning and deep learning is the requirement of high processing power. A potential remedy to this limitation is the adoption of cloud-based platforms that provide flexible infrastructure, load balancing, and services. But the implementation with cloud computing also suffers from real-time processing. The quality of data is also another concern for efficient data-driven solutions. To overcome this limitation, some programmatic data generation approaches that help to generate synthetic data have been suggested by researchers. A wide range of classification and regression algorithms are used for data analysis. Various algorithms such as SVM, RF, fuzzy logic, multiple linear regression, and DT [52], have been utilized to analyze the data accurately. Each algorithm has its own merits and demerits. Linear regression is the simplest method, but its performance level is low. RF models fix the issue of variable collinearity, but the possibility of overfitting is a concerning point. Due to these different limitations, the selection of the most appropriate algorithm to analyze the data is very difficult.

6.5 Decision-making and recommendation

In a smart agriculture system, the capacity to transform data into some knowledgeable form is one of the main features used by the stakeholders to improve decision-making. However, transforming data into some knowledgeable actions required real-time processing. After the evaluation, decision-making processing comes with some limitations including accessibility, scalability, interoperability, uncertainty, etc. Moreover, accessibility is related to the graphical user interface (GUI) [48]. It provides information related to the current status, available information, new tasks, etc. It hides the complexity and allows farmers to manage activities easily. Thus, the interface is an important component that improves accessibility in decision-making. However, more consideration to address this issue in the decision and recommendation systems is required.

Scalability in agricultural decision support systems addresses extendibility. It means extra features are added to the decision support system enriching the overall functionality of the current system. In ADSS, attention needs to be placed on scalability because the employment of multiple models to generate new strategies can enrich the overall functionality. In this, interoperability is also one of the important concepts that emphasize the integration of heterogeneous knowledge into a single ADSS [73].

Uncertainty in the decision and recommendation system may cause unwanted results. It is considered during the runtime and different from the suggested/predicted opinion. Some variable factors in agriculture such as climate change, water potential, wind speed, rainfall, temperature, radiation, and humidity generate tremendous effects. For example, rainfall can change the irrigation frequency. Conclusively, this factor required further improvements to deal with the related issue.

6.6 General issues

Controlling tasks like irrigation, weed management, and pest management required some specific hardware. There are several setups and processing costs associated with smart agriculture system deployment. These generally include hardware costs such as those costs associated with base station infrastructure and sensors [24]. The hardware may be sensors, cameras, and other electronic devices. Varieties of professional and good-quality sensors are required to be deployed on the farms for continuous monitoring. However, a lack of good quality sensors becomes an obstacle in agricultural monitoring. So, sensors with good quality and high reliability are required for real implementation [61]. These devices are costly. Other than these cloud services, network services continuously require subscriptions. The extensive cost of these hardware devices in agricultural activities has required the active consideration of researchers and enthusiastic capitalists to show interest in funding for bulk manufacturing.

Furthermore, the unclear ownership of data and the education level of farmers are also major constraints for smart agriculture development. Farmers feel that their farm-related data are crucial and numerous businesses might want to obtain information from those values without compensation [18]. To mitigate these situations, corporate standards and laws are required to encourage farmers to adopt new ways of data utilization. Additionally, the situation requires some engagement and clear initiatives so that the farmers can participate with common data repositories for additional trust. The economic condition of farmers may also be a main constraint that becomes an obstacle to the adoption of smart agriculture systems.

Other than these challenges, the education level of farmers is not satisfactory. The farmers do not have much understanding of the latest technologies and feel it hard to deal with them. The successful application of advanced technologies to agriculture has a big impact on agriculture but researchers have noted that artificial intelligence technologies already have a big impact on the workforce. Some simpler and more repetitive tasks are being replaced by AI-driven approaches. This will probably lead to a shortage of jobs in the agriculture sector.

7. Observation and Future Directions

A broad literature on artificial intelligence that is applicable in different fields of agriculture is presented. Several methods with the related technology are tested to get the best-suited output with challenges summarized in this literature. This review provides the foundations to direct readers to improve traceability, visibility, engagement, and decision-making in agriculture systems. Data analysis with the help of deep learning and machine learning has successfully been implemented by researchers in weed management, water management, soil management, disease and pest management, and crop prediction. But some associated challenges related to data are of the main concern. A moderately sized dataset for model training is an important aspect to be dealt with. If the size of the training dataset is too small, the accuracy of the model will not meet the desired output. On the other hand, if the dataset is too big, it drastically affects the required resources to train a model. In this way, technology such as MapReduce can be used to overcome these challenges [74]. The requirements of the dataset are critical points of concern. Training a model with a small dataset leads to overfitting problems and even training with data augmentation increases the complexity of the model [75]. The selection of hyperparameters, optimization algorithms, and loss functions directly impacts the performance of models. Therefore, the selection of an authentic dataset [72] and algorithms to choose the right parameter such as Bayesian optimization [76] and neural architecture search (NAS) [77] help to obtain the best-suited accuracy to overcome these challenges. IoT is another approach that has successfully been employed in the agriculture field. It required lots of physical devices or processing units to control the agricultural environment. Optimizing power consumption and dropping costs are one of the main challenges faced by the researchers. The mass production of IoT devices and reduction in physical sizes may help to overcome such issues [33]. In IoT, security challenges are one of the biggest issues. In this, blockchain-oriented technology enhances data transparency and security [78].

Finally, it is essential to ensure that the engagement of farmers must be performed on all levels. Attempts to solve challenges such as waste reduction and food loss should be done at a holistic level with sustainability. In this direction, improving the adoption and engagement in smart farming activities should not be restricted to training and awareness campaigns. Instead of these, some innovative ways and incentives should be given to the farmers for agriculture digitalization.

8. Conclusions

In smart agriculture, lots of advancements are still pending. AI can enhance the farming experience, help to minimize production costs, maximize profit, and help farmers to manage their production. Various difficulties can be handled by utilizing different technologies. AI allows farmers to collect farm-related data and build plans to enhance their effectiveness. It also allows real-time assessment of associated data and boosts operational efficiency. In this study, we described in detail different subfields of agriculture where some advancements are still required. We also demonstrate a smart framework for agriculture development. The authors observe that multiple artificial intelligence techniques are applicable in agriculture. However, the adoption of these new smart technologies still poses considerable challenges.

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