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REVIEW

Recent AI-based smart farming for monitoring and security in sub-Saharan Africa regions

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Artificial intelligence (AI) has revolutionized smart farming in sub-Saharan Africa, especially in Nigeria, which still relies mostly on agriculture with conventional methods, which suffer problems such as pest infestations, erratic weather patterns, and threats to farm security, decreasing productivity. The agricultural practice continues to be an important sector in sub-Saharan African regions, especially West African countries such as Ghana, Cameroon, Mali, Cabo Verde, Nigeria, etc., contributing meaningfully to the economy and serving livelihoods for a large proportion of agriculturalists of the population. The emergence of AI-powered smart farming provides enabling ways to monitor and protect agricultural processes in the regions. This review paper highlights how AI-based technologies such as machine learning, computer vision, Internet of Things sensors, and drone surveillance contributed to the improvement of precision farming, crop health monitoring, and possible real-time threat detection. The study further discusses AI in farming monitoring and farming security. In addition, challenges and solutions of AI technology for smart farming were discussed. The implication of this study will ensure that the agricultural practice receives a technology-enabled framework to foster the acceleration of AI-driven capacity building, digital infrastructure investment, and legislative assistance to enable a seamless practice. The advent of smart farming can transform Africa's agricultural sector, which can lead to resilience and economic growth variability.

Keywords: artificial intelligence, food security, smart farming, farming monitoring, sub-Saharan African

Introduction

Agriculture is a viable sector that is poised to improve the economic development and gross domestic product (GDP) in sub-Saharan African nations, such as Cameroon, Burkina Faso, Kenya, Nigeria, and others that still rely mostly on agriculture. According to the World Bank, for instance, in 2020, about 24% of Nigeria's GDP came from agricultural products (1). This reveals its momentous contribution to economic action and the livelihoods of millions of people practicing agricultural farming in sub-Saharan African nations. Agriculture is indispensable to providing food security in an expanded population of sub-Saharan African nations, especially Nigeria. The agricultural sector continues to remain a hub for the production of a variety of food crops such as cassava, rice, maize, beans, and yam, to yield more for the smallholder farmers to lessen dependence on importation and food security (2, 3). This occurs despite poor infrastructure and climate change, such as extreme weather (4). Agricultural approaches are viewed as becoming more vital to address the inherent issues of food security in the nation. More importantly, agriculture's vital economic contribution to the country of Nigeria is in the area of job creation, self-reliance, and resilience, especially in the rural areas. For example, a few agricultural workers are smallholder farmers, highlighting the industry's serious role in addressing poverty and encouraging socioeconomic growth and development (5). Also, commodities cash exports such as palm oil, rubber, and cocoa contribute a lot to economic variability in Nigeria's foreign exchange earnings. To ensure the optimization of foreign exchange earnings, it is essential to diversify agricultural exports and improve the net value of raw agricultural output (6). The use of emerging technologies such as artificial intelligence (AI), big data analytics, drones, autonomous machinery, sensor technology, and the Internet of Things (IoT), including AI-enabled smart farming, contributes to a creative innovation that exploits agricultural output (7, 8). Smart farming helps farmers to precisely and proficiently monitor and manage many fundamentals of agricultural activities through the use of emerging technology (7, 9). This includes accurate administration of agricultural inputs such as fertilizers and pesticides, especially real-time monitoring of crop health, soil moisture levels, and extreme weather conditions (10).

Smart farming, otherwise known as precision farming, as an organ of agricultural practice, enables farmers to reduce resource waste, boost productivity, and make decisions through the use of automation and data-driven insights (4). This, however, increased yields and profitability of the agricultural industry to support the country's GDP and smallholder farmers (7). Also, the data-driven insights from smart farming enhance the decision-making process by respective bodies such as agricultural development bodies by assisting smallholder farmers in finding patterns, addressing challenges, supporting risk management, and boosting product outputs (8, 11). More so, labor requirements are lowered and operating expenses through smart farming with the use of automation, repetitive mechanisms, and streamlined processes, thereby increasing financial viability (11). With the advent of smart farming innovation, farming methods and food security challenges in contemporary society, including climate resilience and sustainability, will be put to rest (12).

With the introduction of AI-driven technology, significant changes in traditional farming approaches around the world are made manifest and realizable (13, 14). AI is being leveraged to improve agricultural processes in different domains, such as animal management and husbandry, forestation, crop cultivation, and agricultural cyber-extension, which offer unparalleled levels of accuracy, proficiency, and sustainability (10, 15). The two key areas where AI is revolutionizing conventional farming approaches are predictive analytics and decision-making (13). By examining vast volumes of data captured from sensors, satellite images, and other sources of data gathering, AI systems can predict upward trends and downward trends, forecast crop illnesses, and enhance planting schedules. Higher increases in productivity and minimal losses are the results of farmers leveraging predictive skills to protect and facilitate crop selection, irrigation practice, pest control, and decision-making (13, 16). For instance, using ground sensors, drone technology, and satellite images, which are integrated with AI models, farmers can exactly track crop performance, soil moisture intensity levels, and shortage of nutrients in real time (9, 16). Despite its significance, the agricultural industry in some sub-Saharan African countries, like Nigeria, has several difficulties, such as poor infrastructure, restricted access to capital and technology, and disruptions brought on by climate change (17). Government, corporate sector players, and development partners must work together to address these issues. To fully realize the sector's potential, investments in infrastructural expansion, legislative reforms, and agricultural research and extension services are necessary (13). However, because human involvement-based decision-making and participation are convergent, difficulties still exist.

As a result, our study emphasizes how smart farming has the potential to revolutionize agriculture, especially in Nigeria. To achieve efficient farm monitoring and food security, this study primarily contributes to the body of agricultural practice and sustainability in the following ways:

- We provide extensive literature hurting of smart farming within the sub-Saharan African regions using the Nigerian agricultural environments.
- We extensively discuss the AI smart farming technologies to enhance productivity, sustainability, and resilience.
- We present the description, strengths and weaknesses of AI smart farming technologies.
- Also, we discussAI in farming monitoring and security.
- Furthermore, we highlight the challenges and solutions of AI-based methods for smart farming to improve agricultural practices and food security.

The other parts of the paper are structured as follows: Section "Emerging technologies for agriculture" discusses emerging technologies for agriculture; Section "Application of AI in smart farming" explains AI in farm monitoring; and Section "Artificial intelligence in farm security" highlights AI in farm security. In addition, the section "Challenges and solutions" discusses the challenges and solutions of AI technology for smart farming. The concluding remarks are presented in the section "Conclusion."

Emerging technologies for agriculture

One of the newer technologies that is becoming more prevalent in agricultural techniques is smart farming. These methods are based on AI. Drones, machine learning algorithms, and the IoT are some of the smart agricultural technologies that this study highlights. These are covered succinctly as shown in **Figure 1**.

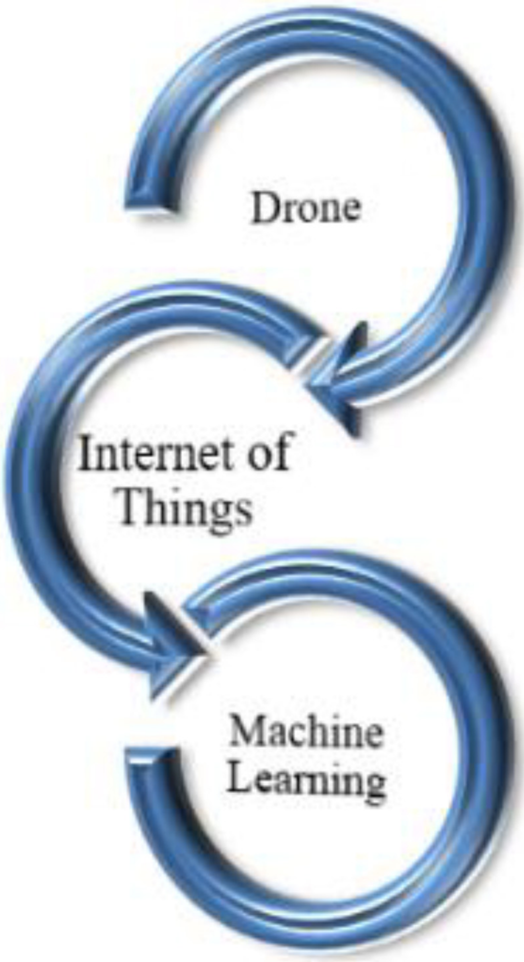

FIGURE 1 | Emerging smart agricultural technology.

Drones

This is often called drones; unmanned aerial vehicles (UAVs) have emerged as a major technology with a variety of uses in agriculture (9, 18). Their versatility, ease of use, and ability to collect high-resolution aerial data have made them indispensable tools for modern farming practices (18). Using drones for crop management and monitoring is one of the most distinctive applications in agriculture. Drones, equipped with higher-resolution cameras and sensors, improve farmers' ability to photograph fields from above and evaluate crop development, pest and disease conditions, and fertilizer and irrigation outcomes (18). Farmers can use this real-time information to make better decisions, use the appropriate amounts of resources on their farms, and take the necessary corrective action to eliminate farm losses (19).

IoT

The IoT is best explained as a network of interconnected physical devices integrated with several sensors and software, combined to assist the devices in collecting and exchanging information or communication (20). In the agricultural industry, the IoT has become a game-changing technology with a wide range of applications that provide creative answers to the problems that farmers face (21). The integration of sensors, actuators, and other internet-connected devices in farming allows for data gathering, analysis, and management to maximize the sustainability of agricultural operations (8, 21). Precision agriculture, where IoT sensors are used to track many parameters such as soil moisture, temperature, humidity, and crop health in real-time sustainability, is the main use of IoT in farming (21). Following analysis, this data offers insights into environmental elements and crop conditions, enabling farmers to make well-informed decisions about sustainable pest control, fertilization, and irrigation (22, 23). Precision agriculture made possible by IoT technology can greatly increase production, decrease resource waste, and improve sustainability by accurately adjusting inputs to the unique requirements of crops (9).

Machine learning techniques

In the growth of modern farming, this subset of AI has emerged out of nowhere and is quickly emerging as a proven strategy that helps farmers solve current issues (15, 22). According to Gavhane et al. (24) 77% of the targeted communications were received by the general population; 94% of people heard information about hand cleanliness, and 80% of people received messages about using face masks. The authors maintained that these algorithms examine data from sensors, drones, satellites, and other sources of massive data sets and provide insightful insights that may be helpful in farming. In the growth of modern farming, this subset of AI has emerged out of nowhere and is quickly emerging as a proven strategy that helps farmers solve current issues (22). Farmers can identify diseases early and carry out focused interventions, lowering production losses and eliminating the need for chemical treatments, by training support vector machine (SVM) models on labeled datasets of both healthy and diseased plants (24). Another well-liked machine learning method in agriculture is Random Forests (RFs). RFs are used in agriculture for tasks involving both regression and classification. RF models use historical data on weather patterns, soil properties, and crop management practices to forecast crop yields for different crops and geographical areas (4). By using this information, farmers can maximize yields and optimize resource use by making well-informed decisions about fertilization, irrigation, and planting schedules (25). The emerging technologies, descriptions, strengths, and weaknesses are presented in **Table 1**.

TABLE 1 | Technologies, descriptions, strengths, and limitations of smart farming.

Author	Technologies	Descriptions	Strengths	Limitations
(8, 26)	IoT	Interconnected devices in farming for data gathering, analysis, and management to maximize the sustainability of agricultural operations.	Real-time monitoring, data accuracy.	Initial setup cost, technical skills
(9, 21)	Drones	Versatility, ease of use, and ability to collect high-resolution aerial data.	Real-time information to make better decisions and use the appropriate amounts of resources.	High initial cost, limited flight time, restricted by regulation
(3, 21, 27)	Machine learning	Examine data from sensors, drones, satellites, and other sources of massive data sets and provide insightful insights that may be helpful in farming.	Identify diseases early and carry out focused interventions, lowering production losses.	Privacy concerns, dependence

Methodology

This study utilizes a literature review methodology. Different articles were searched for from bibliographic databases such as Google Scholar, PubMed, ResearchGate, etc. to retrieve relevant materials, which were downloaded, screened, and analyzed. The various keywords, such as AI, smart farming, farming monitoring, farm security, food security, application areas, and challenges and solutions of smart farming relevant to the subject, were queried and extracted for comprehensive exposition. Conversely, the specific strategic steps were succinctly applied in the research processes: (i) retrieve/download useful materials with necessary detailed information on AI-based technologies utilized for smart farming, security, and monitoring; (ii) precisely synthesizeing and screening of the retrieved articles; (iii) extraction of necessary information related to the AI-based smart farming domain; (iv) some recommendation of the research knowledge to the AI-based Smart Farming Community include (4, 14, 15, 20). The research procedure applicable to the study is shown in **Figure 2**.

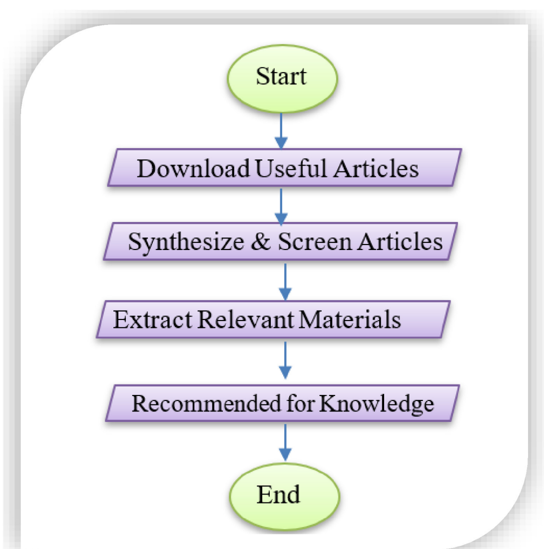

FIGURE 2 | The research procedure.

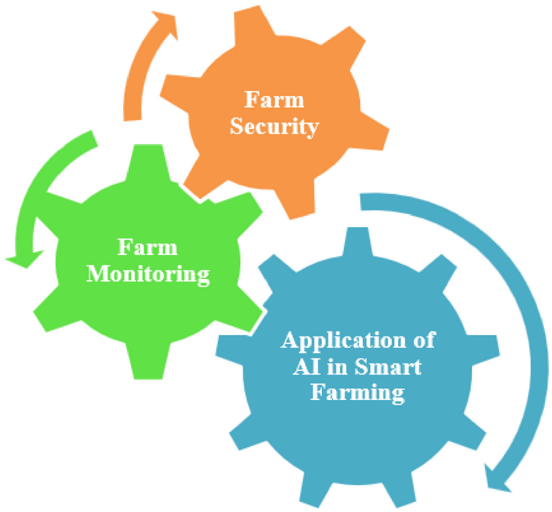

FIGURE 3 | Application of AI in smart farming.

Application of AI in smart farming

In this section, we discussed the application of AI in farm monitoring and security, as shown in **Figure 3**.

AI in farm monitoring

By providing cutting-edge solutions for real-time data analysis, disease identification, yield prediction, and precision agriculture, AI is transforming crop monitoring (28, 29). Farmers can now monitor crops more effectively, make data-driven decisions, and allocate resources more efficiently thanks to AI-driven solutions. Through the use of AI-enabled technologies such as machine learning algorithms, computer vision, and sensor technology, numerous AI applications for crop monitoring have emerged (6, 7, 29). For instance, AI in agricultural monitoring helps to detect and diagnose plant diseases, pest attacks, etc. AI systems using deep learning, such as Convolutional Neural Networks, look for indications of crop disease and pest infestation, including nutritional deficiencies, through images acquired from mobile devices, satellites, and drones. Farmers can prevent production fatalities, pledge custom-made treatments, and identify earlier diseases using AI algorithms trained on massive datasets of annotated images (4, 30, 31).

Furthermore, product harvest increase in agriculture can be predicted using new technology such as AI, which uses metadata extracted from the weather, soil texture and its condition, crop growing stages, and management technological approaches (8). Going forward, by the study output, machine learning algorithms such as RFs and support vector machines can predict the yield for crop farming. For instance, Huang et al. (18), in aggregation with yield history and geographical information system datasets, enable the prediction of future yield fluctuations and crop sowing times. The study maintained that AI models or technology can boost the overall product output of farmers. The studies further ensure that precision agriculture, which highly supports some important inputs such as fertilizer, water, and pesticides, including real-time data, is an additional noteworthy claim of crop monitoring in real practice. Moreover, AI technology deployment in smart agriculture utilizes insight from IoT devices, satellites, and weather station datasets for monitoring nutrient density, soil moisture, and the activity of insects (18). People like farmers may take care of site-specific farming practices that will give healthy agricultural yields without harming the environment by using AI in combination with automated machinery and actuators.

Additionally, AI technologies help to promote sustainable agricultural practices by automating weed detection and intervention, reducing the need for manual labor, increasing productivity, and optimizing the use of herbicides (32). Sensor-based data gathering requires three essential processes: data collecting, data processing, and data transfer (33). To collect the many parameter values about the properties of soil that are optimal for agricultural development, a variety of sensors are used. The data is gathered using a range of sensor devices, such as an electromagnetic sensor, a pH sensor, a salinity sensor, and a soil moisture sensor. The Raspberry Pi 3 system is used here to handle inputs from a variety of sensors because it has the most efficient CPU in comparison and supports IEEE 802.11 wireless standards (29). After that, a cloud is used to store the data. There is also a Wi-Fi facility provided for sending data from the far agricultural area. The data is moved to the cloud for better management via the Internet. The saved data is analyzed using machine learning, and the cloud service used is Amazon Web Services (AWS). The local computer can access the data through the cloud service. To guarantee accurate results, the algorithm is developed inside the machine and assessed using the data gathered. The Raspberry Pi controller is used to collect data from several sensors throughout a single sample period. The average data is then sent via the Internet to the AWS Cloud Network from many sensors.

AI in farm security

AI is widely employed in the security sector on farms, where it aids in efficient surveillance, early detection, and prevention of threats, including trespassing, theft, and vandalism. The study's conclusion is supported by a few previous studies. For instance, Kalkidan et al. (34) carried out two empirical leadership studies to look at the relationship between organizational enlightenment, the outcome variable, and leadership. AI-driven advancements give farmers a new means of efficiently protecting their cattle and farmland. AI is being applied to farm security in a variety of methods, including sensor technologies, computer vision, and machine learning algorithms (35, 36). One use of AI in farm security is the real-time monitoring of agricultural properties through surveillance systems that use computer vision algorithms (34). In order to feed live footage of the activities and monitor for any suspicious activity or human or animal trespass, these devices use cameras placed across the countryside. Locals believe that these herbs can be useful for both traditional treatments and animal husbandry (34). By implementing AI-based object recognition and anomaly detection, farmers can be alerted quickly to security breaches and take preventative measures. Additionally, drones with AI capabilities are increasingly being used for agricultural property patrols and aerial surveillance (37). These UAVs equipped with cameras and AI may fly over large farming regions, surveying farmer-owned land and looking for signs of instability. They used the Kawasaki et al. (37) conceptualized value proposition canvas to highlight their new product and differentiate it based on pricing, product quality, speed, reliability, and features. Farmers may detect any type of breach, including downed fences, unnecessary vehicles, or people, by using drones equipped with AI. Appropriate action can be taken in response to envisaged new security threats from the system. AI is also employed in the creation of smart fences, which employ sensors to identify attackers and software like machine learning.

Furthermore, predictive analytics technologies driven by AI are employed to assess and mitigate security risks on farms (38). To find trends and forecast likely security threats, these systems are prepared to analyze data on past security incidents, meteorological conditions, and seasonal variations. Accordingly, Dinwiddie et al. (38) study on elder abuse and neglect revealed that these crimes are horrifying and common among senior citizens. These observations assist farmers in implementing preventive measures, such as installing sufficient illumination, replacing door locks, and hiring security guards, to shield their crops from pest and disease attacks, particularly during susceptible periods. One of the security and privacy components of smart farming is multi-layered architecture. There are four layers to it. These consist of communication, cloud, edge, and physical. Physical sensors and gateway devices, such as drones operating in the air, self-driving tractors, sensors embedded in livestock, or hub devices placed to enable communication between smart objects or with a central cloud, comprise the physical layer and are scattered throughout agricultural farms or greenhouse buildings (39). For local real-time calculations and decision-making, the edge layer is situated close to end users and end devices (14). The centralized cloud layer's computational demand and network load are both reduced. Each node represents a gateway that includes features including data gathering, security monitoring, detection, prediction, and real-time decision assistance. Additionally, after being virtualized in data centers, the cloud layer connects to the other tiers via the Internet. These cloud layer systems usually leverage Platform as a Service (PaaS) architecture, which lets customers focus on running programs and importing data (40). The communication layer also facilitates interaction between the edge and physical layers and provides an interface via which they can communicate with the cloud layer. From communicating soil temperature through a peer-to-peer sensor communication system to transmitting farm monitoring data to cloud data stores via high-speed mobile networks or alerting farmers about crop quality through a wireless ad-hoc topology, the network layer offers a communication channel to connect all other layers (23).

Additionally, many problems with data, permission and trust, authentication, and secure communication affect security and privacy in smart farming (3, 4). As technology advanced, these problems impacted the uptake and use of smart farming. As a result, it made it easier for adversaries to organize cyberattacks. A smart farm's many diverse sensors, devices, and equipment provide enormous volumes of complex, dynamic, and spatial data. If insiders or unauthorized individuals disclose such information, it might be dangerous. Leaks involving agricultural anti-jamming devices could allow an attacker to circumvent security safeguards. On the other hand, farmers may incur large financial losses if competitors or other unscrupulous actors use information that has been released regarding crops, soil, and agricultural purchases. Therefore, one of the primary objectives of a smart agricultural ecosystem's reliable operation is to provide data security and privacy (41). Furthermore, for smart farming to be implemented successfully and widely adopted in agriculture, further considerations that should be kept in mind include authorization, authentication, and secure communication. Verifying that the messages are originating from a trustworthy source and not an adversarial third party is essential in any case. Private farm data, including soil moisture content, crop output, fertilizer cost, and sensitive livestock data, including location, health, and breeding choice information, are sent to the cloud as part of this information exchange. Devices on a smart farming system cannot connect to other services until they have completed the verification process. Old public-key infrastructure authentication methods cannot be justified as viable alternatives since they are usually low-power devices with limited memory, computing capacity, and storage (12, 42).

Cyberattacks are yet another unseen privacy and security issue that affects smart farming. Supply chain attacks, data attacks, network and equipment attacks, and other relevant attacks, including cyberterrorism, cloud computing, and regulatory and compliance violations, are examples of these cyberattacks (43). These diverse threats are a major concern for farmers. For instance, among other data attack issues, farmers are particularly worried about the disclosure of private information since it may be exploited against them in the commodities market. attacks on hardware and networks, such as side channels, radio frequency jamming, botnets, virus insertion, and denial-of-service attacks. Sometimes, radio frequency connectivity—such as satellite or cellular networks—is necessary for smart farming equipment to function. Smart agricultural equipment commonly uses global navigation satellite systems to boost efficiency using tools and processes including auto steering, path planning, seeding, and spray rates. When it comes to malware, hackers use it to infiltrate connected smart IoT devices. Third parties, software updates, and data falsification are all relevant in supply chain attacks. Therefore, a central malevolent system can control these devices, which are linked to the IoT and may be subject to attacks (44). When a vendor or supplier's system is breached and utilized to steal information from farmers or users, it's known as a third-party data breach. The attacker can then alter the smart farm report and results to suit their needs or benefit. Furthermore, the way smart farming functions is impacted by cloud computing and cyberterrorism assaults. For example, a large percentage of cloud-hosted virtual machines are set up similarly since auto-scaling has gained popularity. In the unlikely event that any of the other virtual machines are compromised, all auto-scaled virtual machines may be vulnerable to attack. Similarly, considering that cyberterrorism is a relatively inexpensive endeavor with enormous return potential, the threats of agroterrorism are too big to ignore (45).

Challenges and solutions

In this section, we discuss the challenges and solutions surrounding the utilization of smart farming-enabled AI technologies in sub-Saharan African regions.

Extreme initial startup costs

Many Nigerian farmers, particularly smallholders with low resources, find it difficult to integrate AI technology into their farming methods because of the large initial investment needs (13). In addition to continuous technical support and maintenance, AI-driven systems usually necessitate expenditures in sensors, data analytics platforms, hardware, and software. Some farmers may likely be reluctant to push investment in innovative AI technology since there is no guarantee for the immediate return on investment and fear of safe investment. This can be exceptional if there are options for financial affordability, indemnity, insurance, and incentives to cover early investment costs, as some farmers cannot afford the AI systems solutions due to limited capacity, knowledge, and competitiveness (13). Most importantly, solutions to these fears and challenges, collaborative methods through the involvement of government support, philanthropic participation, incentives and subsidies from innovative premium waiver offers, public-private partnerships, and high-level educational participation are needed. Putting the local agricultural farmers into context and resource constraints, personalized AI technology will achieve maximum success, scalability, operability, and adaptability.

Lack of technical skills, manpower, and awareness

AI techniques are improving farm practices through crop forecasts and predictions of yield increases (46). Farmers may be hesitant to embrace AI technology if they lack proper training and awareness-raising campaigns because they are concerned about its complexity or efficacy. Providing all-encompassing training and advocacy is important to raise awareness campaigns of the peculiar and raise enough manpower development to match the emerging farming techniques operations.

Controlled access to infrastructure and connectivity

Sub-Saharan Africa's agricultural industry will benefit from AI technology's ability to provide long-term solutions, which will help to reform farm productivity and increase the efficiency of farmer resources. Although there are many benefits to integrating AI into farming practices, there are a few considerations to make before leveraging AI technology in agriculture to its full potential. This study lists the primary challenges of incorporating AI technology into agriculture in sub-Saharan Africa and offers potential solutions. In this way, it is possible to resolve the channel confusion caused by inadequate infrastructure and connectivity, which is particularly noticeable in rural areas where most farmers live.

Another significant challenge faced by farmers with the introduction of AI technologies is the inability to efficiently handle some technological mechanisms, such as cloud-based analytics, remote monitoring systems, and real-time data. These challenges are caused by fluctuations of power supplies and low internet connectivity signals. Alhassan et al. (47) noted that AI benefits are realized to have contributed to enhancing productivity and decision-making without infringement on infrastructure and its connectivity. Also, Adesina et al. (46) pinpointed that regional farmers lack technical manpower, knowledge, and prior experience, which is important to the use of AI technology for agricultural development and implementation. Thus, the availability of infrastructure and internet connectivity of the internet would help to address the inherent issues being experienced.

Conclusion

AI technology for farm monitoring and security processes is well-suited for sub-Saharan Africa, especially Nigeria's agricultural sector. The agricultural industry, more importantly, smart farming, cannot be underestimated because it makes farm security and monitoring seamless by boosting farmers' product outcome, minimizing losses, as well as protecting the farmer's livelihood from impending risks. Nigeria requires smart farming practices to achieve sustainability, economic growth, and food security. The study discussed smart farming and AI smart farming technologies to enhance productivity, sustainability, and resilience. In addition, in this review paper, the strengths and weaknesses of AI smart farming technologies were highlighted, including AI in farming monitoring and security. The study further enumerated the challenges and possible solutions of AI-based methods for smart farming to improve agricultural practices and food security.

The implication of this study would ensure that government agencies, policymakers, farmers, and the academic community leverage emerging technologies such as AI, the IoT, sensor technology, and more to formulate, analyze, and apply a real-world decision to overhaul the agricultural practice challenges in sub-Saharan Africa and increase productivity.

Availability of data and materials

Not applicable.

Code availability

Not applicable.

Ethics approval and consent to participate

The authors certify that the study was performed in accordance with the ethical standards.

Consent for publication

No applicable.

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Conflict of Interest

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