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TOPICAL REVIEW

Smart Agriculture: Current State, Opportunities, and Challenges

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ABSTRACT Smart agriculture or precision farming is a rapidly evolving multidisciplinary field encompassing knowledge from agriculture, technology, data science, and environmental science to name a few. Amidst the large number of recent research publications related to smart agriculture and intelligent farming practices, a need arises to summarize their findings in a single consolidated review article. This work endeavors to summarize recent key technologies and applications of smart agriculture, delineate the prevalent challenges it faces, highlight its publicly available datasets for adoption, and offer some policy guidelines for stakeholders, assisting them in making informed decisions regarding technology adoption and investment. We conclude that smart agriculture can potentially revolutionize the agricultural sector, provided we overcome the challenges by ensuring effective collaboration among stakeholders, a strong infrastructure, digital literacy, adoption incentives, data privacy, interoperability, favorable policy frameworks, and continuous research and development.

INDEX TERMS Smart agriculture, precision agriculture, agricultural technology, agricultural datasets, IoT in agriculture, smart sensors, applications of smart agriculture, success stories in agriculture.

I. INTRODUCTION

Smart agriculture (SA) proves to be a transformative paradigm in modern farming practices, using cutting-edge technologies to increase efficiency, productivity, and sustainability [1]. At its core, SA integrates a diverse array of technological components, starting with the deployment of sensors and Internet of Things (IoT) devices. SA operates on key principles such as optimization of resources, precision and accuracy in farming practices, data-driven decision-making, sustainability, and integration with market access platforms [2]. The key application areas of SA include crop growth, crop monitoring, livestock management, irrigation management, pest and disease control, supply chain optimization, and farm management systems etc.

In the 1980s, the use of GPS technology laid the foundation for precision farming, enabling farmers to map and manage their fields with unprecedented accuracy. The rise of the IoT and sensor technologies ushered in an era of real-time data collection from fields, enabling farmers to observe soil conditions, crop health, and weather patterns more comprehensively [3], [4]. The widespread application of artificial intelligence (AI) and machine learning in agriculture during the 2010s was a major advancement, where advanced analytics empowered farmers to make decisions based on data, optimizing resources and increasing productiveness. Drones and robotics gained prominence, automating various farming tasks and further enhancing precision [5], [6]. Thus the evolution of traditional farming into a technology-driven approach represents a profound shift in agricultural practices, enhancing efficiency, sustainability, and productivity. SA is continually evolving, integrating advanced technologies to optimize farming processes [7]. The emerging trends collectively aim to revolutionize farming methods to make them more effective, sustainable, and capable of meeting the increasing global food demand while minimizing the environmental impact [8]. Figure 1 shows an overview of SA.

In [9], the three main development modes of SA i.e. facility agriculture, precision agriculture, and order agriculture are discussed, along with the key technologies,

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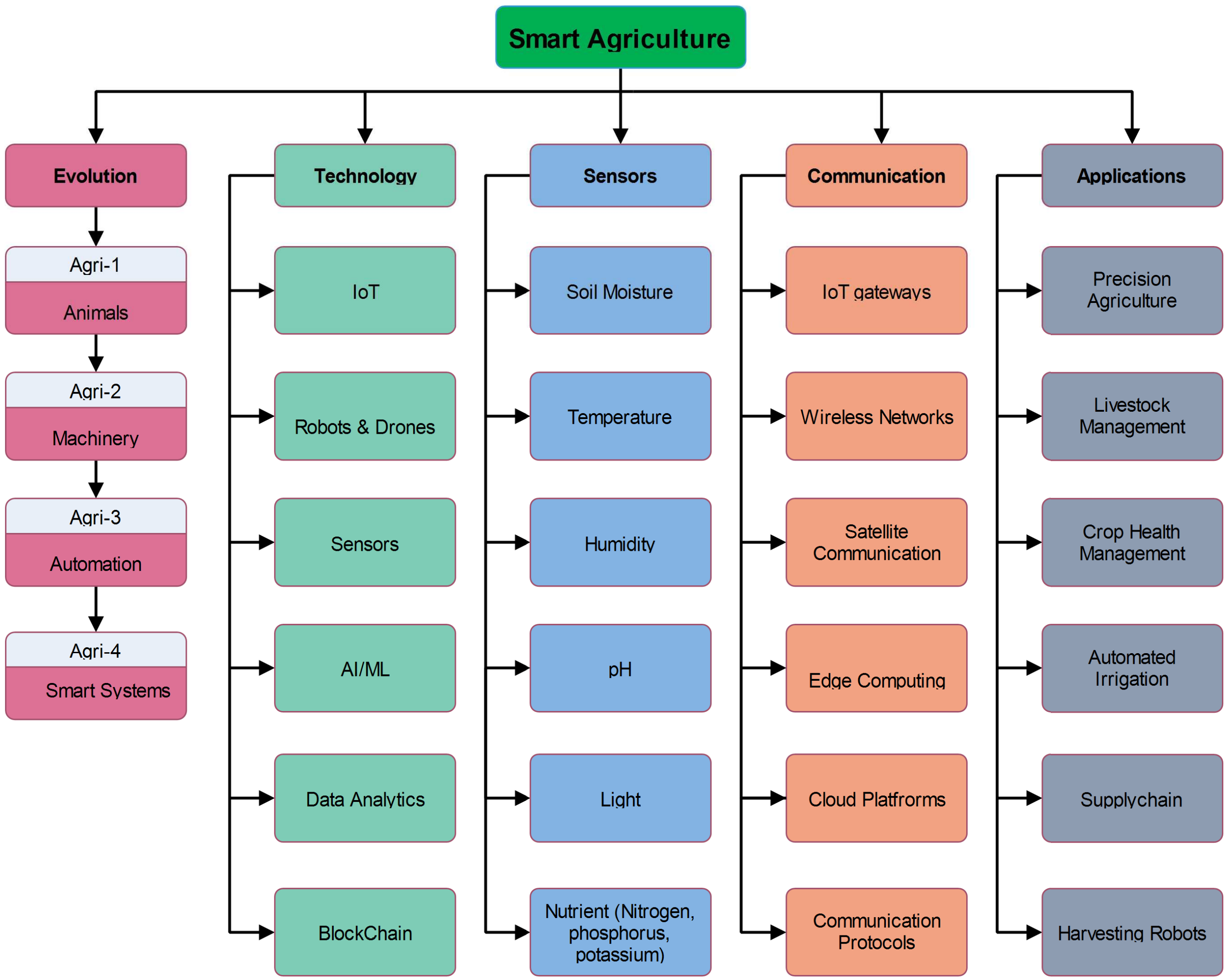

FIGURE 1. **Smart agriculture at a glance.**

applications, and security measures for each mode. From the perspectives of information technology and agricultural productivity, the security issues associated with SA are examined. Reference [10] explores the challenges and opportunities of SA related to environmental sustainability, economic viability, and social acceptability, as well as recent advancements in technologies like AI, cloud computing, big data analytics, blockchain, and IoT. Reference [11] focuses on the role of the IoT in SA, providing an overview of surveys and emerging agricultural IoT technologies including unmanned aerial vehicles, cloud/fog computing, software-defined networking, open-source IoT platforms, wireless technologies, and middleware platforms. Research gaps and future directions for agricultural IoT are also identified.

Despite being available in abundance, the existing literature on SA lacks comprehensive coverage of all related aspects, presenting a gap that this research aims to address. Table 1 summarizes focus of the existing survey articles in comparison to this work, and demonstrates the vast coverage of topics this manuscript promises. Our motivation behind this attempt is KNePSTreC-driven, which stands for advancing *Knowledge* on smart agricultural practices through effective *Networking* with our peers, influence *Policy* decisions, promote *Sustainability*, identify emerging *Trends*, and address critical *Challenges* in SA. Figure 2 reflects our KNePSTreC framework. This study endeavors to provide a summary of recent advancements, benefits, challenges, datasets, emerging trends, and technologies in smart agriculture, all consolidated within a single review article – making it an encyclopedia on SA.

For this survey, we have employed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology. A literature search was done in the Science Direct Freedom Collection, Elsevier database, Web of Science - Core Collection, MDPI – Open access, and Springer Link Journals using the flowchart and the list of items of

TABLE 1. Comparison with the existing survey articles.

Sr. No.	Reference	Year	Technologies	Applications	Challenges	Datasets	Success Stories	Future Trends
1	[3]	2021	✓					
2	[9]	2021	✓	✓	✓			✓
3	[10]	2021		✓	✓			
4	[11]	2021	✓		✓			✓
5	[12]	2022	✓	✓	✓			
6	[13]	2021	✓	✓				✓
7	[14]	2020	✓		✓			✓
8	[15]	2020	✓					✓
9	[16]	2022	✓		✓			✓
10	[17]	2020	✓		✓			✓
11	[18]	2020	✓		✓			✓
12	[19]	2023	✓					
13	[20]	2021	✓		✓			✓
14	[21]	2021	✓					✓
15	[22]	2021	✓	✓				
16	[23]	2024	✓					
17	[24]	2022	✓	✓	✓			✓
18	[25]	2022	✓		✓			✓
19	[26]	2022	✓					
20	[27]	2023	✓	✓	✓			✓
21	[28]	2017					✓	
22	This work	2024	✓	✓	✓	✓	✓	✓

FIGURE 2. KNePSTreC framework summarizing motivation.

this method. Keywords such as smart agriculture, precision agriculture, IoT in smart agriculture, IoT in agriculture, smart sensors, agricultural datasets, success stories in agriculture, and applications of smart agriculture were used to retrieve relevant studies. The searches were limited to the English language only. The research procedure was validated using the PRISMA checklist [29]. The authors identified records based on their titles and abstracts in the first step. Then the exclusion/inclusion criteria were applied to identify eligible records. Each author individually reviewed and resolved any differences in the titles and abstracts of the search results. Articles that discussed SA, PA, IoT in SA, IoT in agriculture, smart sensors, agricultural databases, success stories in agriculture, and applications of smart agriculture were eligible for full-text screening. Disagreements were settled through conversation after full texts were reviewed by all authors for inclusion. Articles that discussed smart agriculture in relation to technological advancement were incorporated into this systematic review. Studies that used administrative or previously gathered data were also permitted as long as they met additional requirements. Studies released prior to 2010 were not included in the analysis.

The survey is organized as follows: Section II offers a concise overview of key technologies and innovations, while Section III delves into application areas. Section IV explores the benefits and challenges associated with smart agriculture, and Section V highlights relevant datasets. In Section VI, the initiatives and success stories in SA are summarized, followed by a discussion on future prospects in Section VII. Finally, Section VIII concludes the survey, encapsulating the key findings and insights gleaned. By presenting this detailed review, our aim is to contribute to the advancement of knowledge and development in SA practices.

II. KEY TECHNOLOGIES AND INNOVATIONS

PA involves utilizing technology to enhance crop yields, decrease resource wastage, and boost overall efficiency by strategically utilizing data, advanced technologies, and real-time information in agricultural management. Key elements include GPS technology, satellite imagery, and sensors for detailed data collection on conditions of soil, weather patterns, and crop health, which is then analyzed through machine learning and data analytics algorithms to produce practical insights. The main aim is to tailor inputs like water, fertilizers, and pesticides precisely to meet the unique needs of each field section, minimizing waste and optimizing resource utilization, while automated machinery and robotic systems are used for accurate tasks like planting, harvesting, monitoring, and maintenance.

PA promotes sustainability in addition to increasing productivity by promoting responsible resource management.

FIGURE 3. **IoT applications in smart agriculture.**

By embracing the PA techniques, farmers can navigate challenges such as climate change, variability in soil conditions, and the need for increased food production more efficiently and sustainably.

A. INTERNET OF THINGS (IoT) DEVICES

An Internet of Things (IoT) device is a physical device that is networked and has sensors, actuators, and software installed in it so that it can gather, exchange, and use data [30]. These devices, ranging from everyday objects to specialized machinery, are designed to enhance connectivity, automation, and making decisions based on data in various domains.

IoT devices are essential in advancing smart farming by gathering data in real time on various factors like soil moisture and animal behavior. This information is transmitted online, enabling remote monitoring and control for farmers [12]. In industries, IoT aids in predictive maintenance, inventory tracking, and energy optimization [31]. These devices also find use in smart homes, healthcare, and transportation, among others, showcasing their transformative impact on different sectors through valuable insights, efficiency enhancement, and convenience [13], [14].

Reference [32] delves into the most recent developments in IoT and sensor technologies for agriculture in addition to discussing their numerous applications. The major applications include crop disease detection, irrigation monitoring, fertilizer administration, processing, logistics, forecasting, harvesting, monitoring climate conditions, and fire safety. Additionally, it presents a variety of sensors that can identify various plant diseases, livestock, moisture, nitrate, pH, electrical conductivity, CO_2, temperature, humidity, light, weather station, water level, and flexible wearables. Figure 3 shows some IoT applications in SA.

Debnath and Saha [33] introduces a novel approach to SA by integrating IoT network with Machine Learning. The main innovation lies in its capability to identify brown-spot disease in rice paddies at an early stage, utilizing Convolutional Neural Networks (CNN) for the first time. Instead of the conventional methods, this project employs Deep Learning. It utilizes real-time data for image recognition and preprocessing. The pre-processing of data and feature extraction stages are facilitated by a custom image-processing tool. Additionally, an accompanying mobile application has been developed to provide farmers with access to this technology.

Sarpal et Al. [35] address the challenges facing agriculture, particularly in terms of low-yield production, due to limited infrastructure and resources. To overcome these challenges, the paper proposes an IoT-driven innovative approach. It introduces a sensor-based irrigation model that collects and analyzes data in the cloud for real-time monitoring. This data is then integrated into an Android application, providing farmers with an easy-to-use interface. The application allows farmers to manually control their farms or set timers for automated irrigation. Additionally, a Machine Learning model predicts suitable crops based on varying weather conditions. The application also includes a classified portal for direct buying and selling between farmers and customers, eliminating the need for intermediaries. A unique aspect of this research is the monitoring and control of farm equipment and crop prediction through a locally installed LCD display and keypad in farmers' homes. Overall, the proposed framework aims to enhance agricultural productivity, improve farmers' livelihoods, and contribute to economic growth in the nation in an energy-efficient and user-friendly manner.

Gia et al. [34] have incorporated Edge and Fog computing, which involves processing data closer to the source, which is crucial for expanding functionality. In order to improve the capabilities of SA and farming applications, this study presents a system architecture and implementation that integrates AI at the local network level, or Edge AI. This is achieved through the utilization of Edge and Fog computing along with LPWAN technology for broad coverage. A sensor node, an Edge gateway, cloud servers, LoRa repeaters, a Fog gateway, and an end-user terminal application make up the suggested system. In particular, the study recommends using a CNN-based image compression technique at the Edge layer to provide data in a single message from several sensor nodes that are within the gateway's range. Advanced compression methods are employed to significantly reduce data size, up to 67%, while maintaining a low decompression error rate of below 5%. This innovative approach offers a novel solution for handling IoT data effectively. The system is depicted in Figure 4.

Avcsar and Mowla [24] have thoroughly discussed five wireless communication protocols used in six diverse SA applications. They point out four challenges facing the SA adoption, especially in the context of wireless communications. They believe that 1) cost, mainly driven by hardware resources and maintenance, 2) system security, 3) quality of communication, and 4) optimal system design are the primary challenges that still demand addressing. The authors further deliberate on the future trends in SA applications, which according to them, will mainly be driven by the quality and efficiency of communication. In another survey [27] Mowla et al. have collected a large number of recent works on the role of IoT and wireless sensor networks in the SA applications.

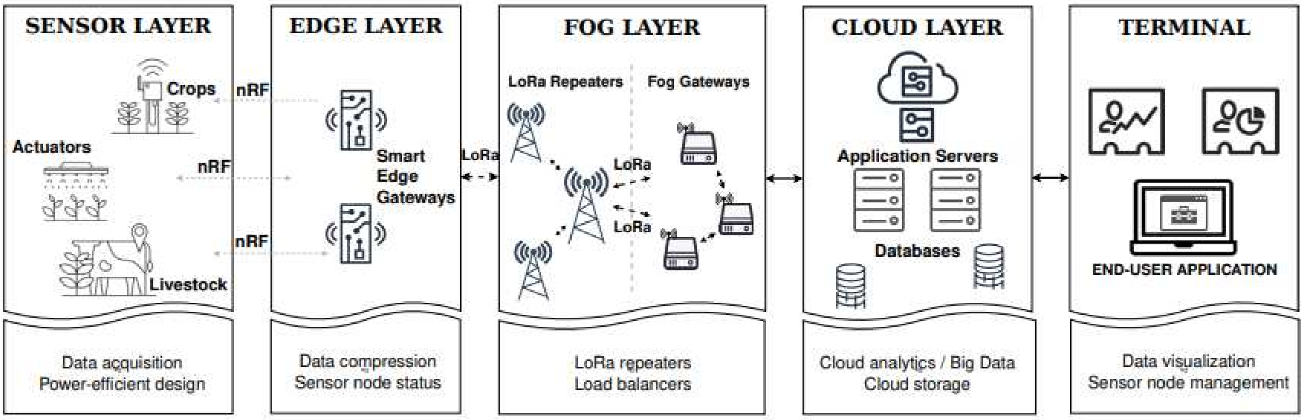

FIGURE 4. 5-layer Sensor-Edge-Fog-Cloud-Terminal SA [34].

B. ROBOTS AND DRONES

Robots and Drones are revolutionizing SA by providing farmers and agronomists with advanced monitoring capabilities through aerial cameras and sensors. Robotics plays a vital role in the realm of SA, assisting in a new era of precision, efficiency, and automation. Agricultural robots are built to perform a multitude of functions, from planting and harvesting to weeding and monitoring, contributing to optimized farming practices [36]. In SA, robotic systems offer several advantages. They enhance operational efficiency by automating labor-intensive tasks, reducing dependence on manual labor, and mitigating labor shortages. Precision is a hallmark of agricultural robotics, with machines capable of precisely planting seeds, applying fertilizers, and performing other critical operations with minimal wastage [16].

Reference [15] provides an overview of apple harvesting robots, including their development, structure, and operation process. It explains the principles behind apple harvesting robots and summarizes research on target fruit recognition, all-weather operation, and intelligent computing theory. The focus of research on apple harvesting robots is improving efficiency.

These robots can navigate fields autonomously using GPS technology and advanced sensors, ensuring accurate and timely execution of tasks. By adopting robotic technologies, farmers can improve productivity, optimize resource utilization, and respond effectively to the challenges posed by climate change and evolving agricultural demands, thereby contributing to a sustainable and technologically advanced future for agriculture [17], [37].

Dharmasena et al. [38] introduce an automated system designed to efficiently manage climate and irrigation within a greenhouse. The system employs a cloud-connected mobile robot capable of monitoring humidity, soil moisture, temperature, and pH levels. Through image processing, the robot can detect unhealthy plants. Based on sensor data, a fuzzy controller controls the irrigation, humidifiers, and cooling and heating systems of the greenhouse. While onboard sensors record information about the surrounding climate, the mobile robot explores a pre-drawn greenhouse layout and gathers soil samples for analysis. Additionally, a robot-mounted camera captures images of the plants, allowing for detection of unhealthy crops utilizing leaf color and texture. Sharma and Borse [39] extensively outline the design and development of an autonomous mobile robot tailored for agriculture or plant nursery applications, encompassing plant disease detection, growth monitoring, and spraying functions for pesticides, fertilizers, and water. The proposed platform offers a compact, portable, and robust solution capable of autonomously surveying farmland. It efficiently identifies diseases, monitors plant growth, and administers appropriate measures such as spraying pesticides, fertilizers, and water as needed, enhancing overall crop management processes.

Similarly, Drones offer a detailed perspective of agricultural areas, allowing for precise data collection and analysis [13], [40]. In SA, drones are utilized for various tasks such as monitoring crop health, assessing irrigation systems, and creating detailed field maps for PA practices [41]. Farmers may make better crop management and more informed decisions thanks to the real-time data collected by drone flights, and enhance productivity while promoting sustainable farming practices [42]. Figure 5 shows drones in SA.

In [43], authors gather corn field images weekly on a multi-spectral band using UAV and CubeSat from Planet Lab. They conduct various measurements with 28 nitrogen management treatments and four duplicates for experimentation. They specifically study 11 nitrogen management treatments and report that UAVs as well as CubeSat sensors can identify nitrogen stress before tasselling, and use the green chlorophyll index (CIg) to monitor changes in stress levels for various management strategies. The CIg of UAV data provides more detailed spatial information than CubeSat CIg due to its higher resolution when studying different nitrogen management practices in trial plots.

FIGURE 5. Drone applications in smart agriculture.

Shah et al. [44] suggest an automated method for plant identification utilizing a synthetic neural network capable of recognizing images of plant leaves using drones. The EfficientNet-B3 model is trained, resulting in an impressive success rate in identifying specific combinations of plants and diseases. To enhance accessibility, both an Android application and a website are developed, enabling farmers and users to conveniently detect diseases from plant leaves. Similarly, Kundu et al. [45] emphasize the advantages of employing drones in the identification and visualization of plant diseases. By employing an intelligent and automated data collection and classification system, the process of disease detection becomes more streamlined and cost-efficient. They report that this method holds promise for notably enhancing the precision and effectiveness of plant disease detection and surveillance. Chen et al. [46] have used drones for irrigation systems management. They have achieved uniformity of water distribution for peanuts and cotton crops by using onboard cameras for irrigation uniformity evaluation.

C. SENSORS

Sensors are integral components of SA, driving the collection of real-time data essential for informed decision-making in farming practices. Deployed across fields and livestock, these sensors capture a spectrum of environmental parameters crucial for crop management. Soil moisture sensors gauge hydration levels, while temperature and humidity sensors provide insights into climate conditions [12].

Crop health monitoring is achieved through a combination of various measurements by different sensors, such as moisture, nitrate, pH, electrical conductivity, CO_2, temperature, humidity, light, water level, etc. Crop health is also monitored through sensors detecting chlorophyll levels and nutrient concentrations. Weather sensors offer precise data on atmospheric conditions. Livestock wearables incorporate sensors to monitor animal health and behavior. These devices collectively contribute to the optimization of resources and sustainable farming practices [47].

A camera with a microcontroller, WiFi, smart remote devices, internet access, multiple sensing nodes for interfacing, and sensor nodes in different places are all part of the SA system with IoT [48]. Such sensors include those that measure temperature, monitor soil moisture, use PIR technology to detect objects, people, and animals in the field, and GPS-based remote control robots that perform tasks like weeding, spraying, and moisture sensing.

Electrical conductivity (EC) and pH sensors are crucial to smart agriculture because they allow soil and water conditions to be optimized to maximize crop output and growth. Farmers may use the real-time data from these sensors to make more informed decisions about fertilization and irrigation. EC sensors track salt levels to prevent soil degradation and manage nutrient levels. On the other hand, pH sensors evaluate the acidity of soil and water to ensure optimal nutrient availability. When combined with IoT technologies, these sensors allow for accurate management and automated modifications, encouraging sustainable farming methods and effective use of resources. Farmers may lessen their influence on the environment and increase agricultural output by utilizing this technology.

The advent of these smart sensors has enabled farmers to embrace precision agriculture, tailoring irrigation, fertilization, and pest control based on actual field conditions. This real-time monitoring not only enhances productivity and yield but also optimizes resource application to minimize environmental impact. Sensors in SA exemplify the transformative power of technology, fostering a more efficient, sustainable, and data-driven approach to modern farming [49]. Garlando et al. [50] provide an overview of sensors utilized in SA, categorizing them into two main groups: sensors to measure the health of the plants and the quality of the fruit, as well as sensors to keep an eye on the environmental factors that support plant growth. It is shown that leveraging advancements in electronics and sensor technology is a straightforward approach to achieving various objectives in agriculture.

D. ARTIFICIAL INTELLIGENCE (AI) AND MACHINE LEARNING (ML)

AI and ML are at the forefront of revolutionizing SA, providing farmers with powerful tools to optimize decision-making processes and enhance overall productivity. AI and ML algorithms leverage the large amounts of data gathered by drones, sensors, and other IoT devices in SA systems [51], [52]. In precision farming, AI systems use both historical and current data to forecast agricultural production, optimize irrigation schedules, and identify potential pest or disease outbreaks [53]. Machine learning algorithms can recognize patterns in crop images [54], helping farmers assess plant health and identify stress factors.

Moreover, AI-driven robotic systems perform tasks like precision seeding, harvesting, and weeding, decreasing manual labor and increasing the effectiveness of operations [16].

FIGURE 6. AI applications in smart agriculture.

Predictive analytics based on machine learning can offer insights into market trends and assist farmers to make well-informed decisions regarding the selection of crop and pricing tactics [55]. The ability of AI and ML to adapt enables them to consistently improve and offer farmers precise and customized suggestions. In the ongoing development of SA, AI and ML will be crucial in transforming farming, ensuring it meets the growing worldwide need for food while becoming more sustainable, efficient, and resilient. Figure 6 shows some of the AI applications in SA.

Amara et al. [56] present a method to identify and categorize banana diseases using a CNN model. This approach aids farmers in promptly, economically, and efficiently detecting diseases affecting their crops. The system successfully identifies two banana diseases, Sigatoka and speckle, by analyzing images of affected leaves through a deep neural network model. Albuquerque et al. [57] introduce a deep learning method to identify water needs from aerial images of irrigation systems. This automated detection streamlines the irrigation system management, thereby decreasing maintenance time and costs. Initial findings, utilizing the Mask R-CNN neural network, indicate the feasibility of identifying water in UAV-captured images. The system identifies and prevents malfunctioning irrigation, which could lead to under or over-watering, by effectively implementing irrigation plans.

Deep Learning has been successfully applied for crop classification and disease identification. Reenul et al. [58] have demonstrated that utilizing the attention-based deep network is a viable method for tackling such scenarios, specifically in the realm of weed and crop identification using a drone system. The main goal of this research is to examine vision transformers (ViT) and utilize them for plant categorization in the images captured by Unmanned Aerial Vehicles (UAV). Figure 7 shows an overview of the model utilized. Similarly, Qi et al. [59] have successfully applied a visual attention-based YOLOv5 model to the recognition of tomato disease identification.

Mohyuddin et al. [23] have presented a comprehensive review of machine learning approaches for PA. The readers, exclusively interested in exploring the role of ML and AI in SA, are encouraged to go through the referenced article.

E. DATA ANALYTICS

Utilizing data analytics in SA is crucial for improving agricultural efficiency, providing instant evaluations, and increasing crop yields. The integration of modern technologies such as IoT devices, sensors, UAVs, and blockchain are used to generate vast quantities of data, which necessitate thorough examination to offer a scientific understanding of various factors affecting agriculture, including crop development, soil health, and climate variations. This data allows farmers to identify the optimal timing for planting, fertilizing, and harvesting, as well as identifying specific land areas requiring special attention. Furthermore, data analytics helps improve how resources like water are allocated to reduce waste and lessen environmental impacts. In the end, the use of data analytics in SA offers the potential to transform food production methods, making them more environmentally friendly, efficient, and resistant to challenges such as changing climates [60].

Data analytics assist in assessing the effectiveness and impact of agricultural technologies and practices in SA through essential evaluation metrics. Important metrics encompass crop production, use of resources like water and fertilizers, consumption of water and energy, pest and disease control, soil health, economic feasibility, environmental influence, acceptance of new technology, accuracy and dependability of data, efficiency in operations, and quality and safety of food. Via these measurements, data analytics offer important information for improving agricultural activities, promoting sustainable methods, and informing decisions made by farmers, researchers, and policymakers [61].

Machine learning algorithms process vast datasets, which provide predictive models for disease outbreaks, crop productivity, and efficient use of resources. These insights empower farmers to make strategic decisions, enhancing efficiency, minimizing risks, and promoting sustainable agricultural practices. Data analytics in smart agriculture not only improves operational productivity but also fosters resilience in the face of climate change, ensuring that modern farming remains adaptive, efficient, and capable of meeting the challenges of a rapidly evolving agricultural landscape [18]. The promise of computing technologies such as machine learning, data analytics, wireless sensor networks, and the IoT in agriculture is demonstrated by Akhter et al. [4]. Through the use of data analytics and machine learning within an IoT system, it presents a prediction model for Apple disease in the apple orchards of the Kashmir valley.

Rabhi et al. [62] have shown that addressing irrigation challenges in agriculture is paramount, with a shift from manual to smart irrigation driven by analyzing big data. This paper employs a method that integrates data mining algorithms like support vector machines and neural networks

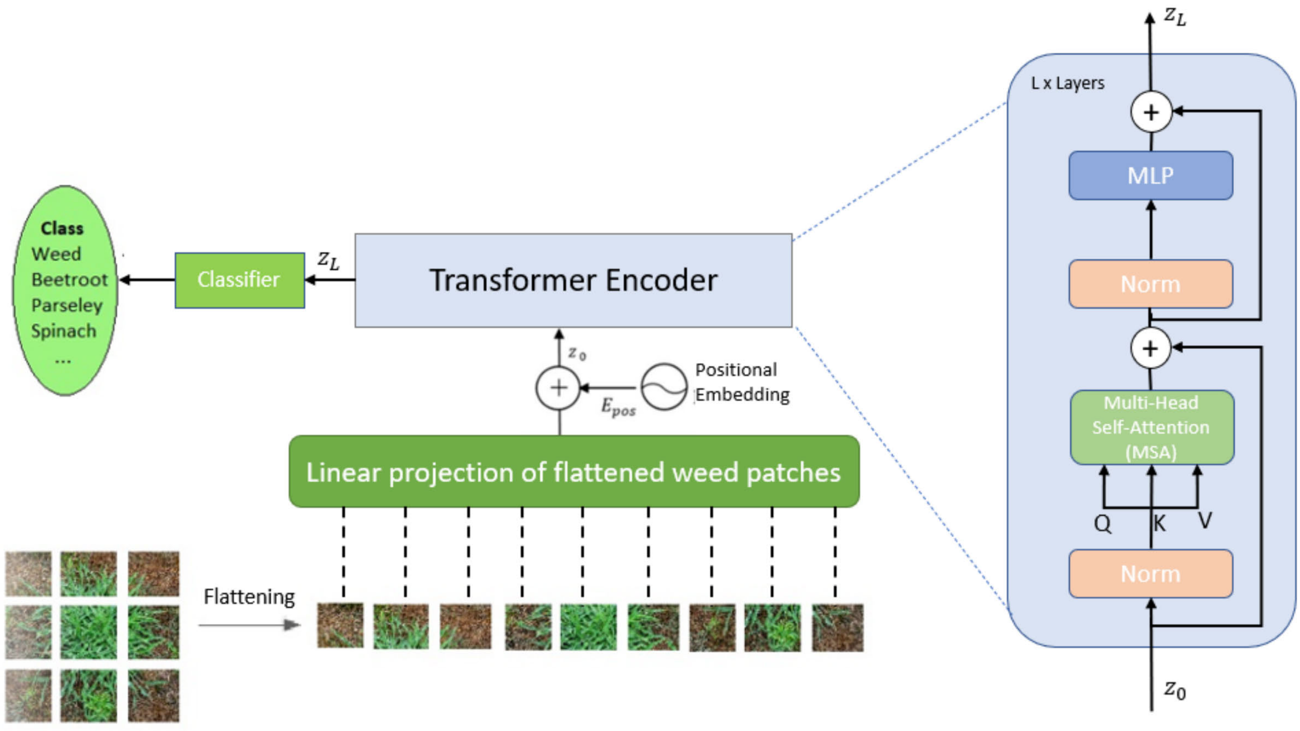

FIGURE 7. ViT model applied in smart agriculture [58].

with remote sensing, and big data. The method entails integrating machine learning with the Apache Spark tool, Databricks, to forecast soil drought by measuring soil temperature and moisture.

F. BLOCKCHAIN

Blockchain technology is increasingly utilized in SA to boost transparency, traceability, and security in the agricultural supply chain. Through blockchain use in SA systems, a secure and unchangeable ledger is created to track all transactions from planting to distribution. This technology ensures data accuracy, minimizes the risk of fraud, and builds trust among stakeholders. Farmers can securely document crop production details, while consumers can follow the journey of agricultural products, promoting accountability and ethical standards. Smart contracts, also a part of blockchain technology, enable automatic and transparent agreement execution, simplifying tasks like payments and quality assurance. By leveraging blockchain in SA, the industry can address challenges related to food safety, fraud prevention, and supply chain efficiency, ultimately assisting in the development of a more sustainable, secure, and reliable global food system [63], [64]. Figure 8 shows some of the blockchain applications in SA.

Kassanuk and Phasinam [65] shows that the involvement of middlemen, such as human-operated agencies, has led to issues like accessibility, efficiency, security, and immutability. This has resulted in financial losses, crop contamination,

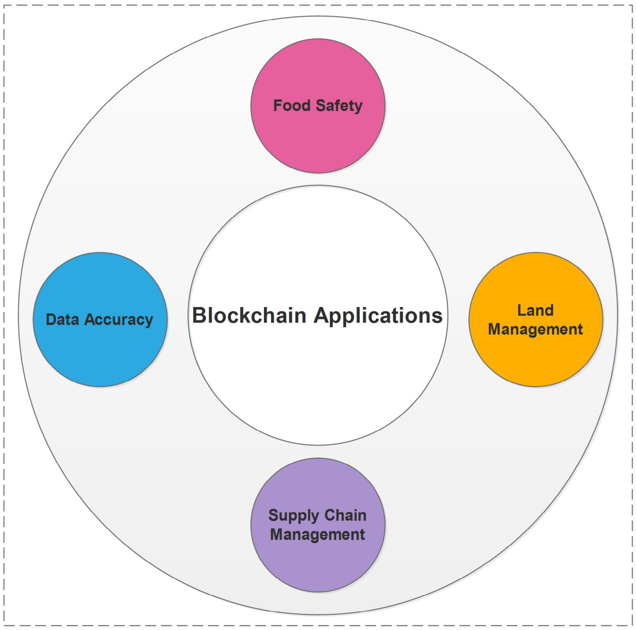

FIGURE 8. Blockchain in smart agriculture.

and waste. Blockchain offers a decentralized ledger that records data from various parties involved in currency transactions. The central network depends on blockchain to record transaction history and related information, including completion status, sender and recipient addresses, and transaction success details. Kassanuk and Phasinam [65] introduce a smart contracts framework employing blockchain. In this system, all participants in the blockchain-driven distribution network manage transactions among each other. To maintain openness and traceability across the whole supply chain ecosystem, all transactions are logged. To detect misuse, a group signature mechanism is employed. The system's overall performance is evaluated based on trust between parties, system risk reduction, and transaction efficiency.

III. APPLICATIONS OF SMART AGRICULTURE

In what follows, we list a number of applications that have been revolutionized by the advent of SA technologies and practices.

A. EFFECTIVE RESOURCE UTILIZATION

SA transforms crop growth by leveraging advanced technologies like IoT, sensors, and data analytics. Sensors monitor soil conditions, humidity, and nutrient levels in real time, providing precise data for informed decision-making [66]. Automated irrigation systems, guided by this data, ensure optimal water usage. Drones and satellites capture high-resolution images to assess crop health, identifying potential issues early [67]. Machine learning algorithms predict crop yields and recommend tailored strategies for planting and harvesting. SA thus fosters more efficient use of resources, reduces its negative effects on the environment, and enhances crop production for sustainable and technologically advanced farming practices [68].

B. REMOTE CROP MONITORING

SA revolutionizes crop monitoring through technologies like sensors, drones, and data analytics. Field-installed sensors gather real-time data on soil conditions, moisture levels, and nutrient content, ensuring precise resource management [69], [70]. Drones equipped with cameras and sensors conduct aerial surveillance, capturing detailed images for early detection of crop health issues, pests, and diseases [71]. Data analytics processes this information, providing farmers with actionable insights. This proactive approach enables swift responses to potential challenges, optimizing crop health, minimizing losses, and eventually assisting in the development of more fruitful and sustainable crop monitoring methods in modern agriculture [72], [73].

C. LIVESTOCK MANAGEMENT

SA transforms livestock management by integrating IoT devices, wearables, and data analytics. Livestock wearables, equipped with sensors, monitor animal health, behavior, and location in real-time. This data is transmitted to a centralized system, allowing farmers to remotely track and assess the well-being of each animal [74]. Automated feeding systems and smart barns further streamline operations, ensuring optimal conditions for livestock. Predictive analytics algorithms help anticipate health issues, enabling early intervention. SA in livestock management enhances efficiency, minimizes resource wastage, and promotes animal welfare, fostering a more sustainable and technologically advanced approach to animal husbandry [75].

D. IRRIGATION MANAGEMENT

SA revolutionizes irrigation management through advanced technologies like IoT and data analytics. Weather data and soil moisture sensors guide automated irrigation systems, ensuring precise and timely water delivery to crops. These systems are capable of being observed and managed remotely, thus optimizing water usage and reducing wastage [76]. Drones equipped with sensors provide real-time aerial views, aiding in the assessment of irrigation effectiveness and identifying areas needing attention. Data analytics algorithms process this information, offering insights for improved irrigation scheduling [19]. SA in irrigation management enhances water efficiency, conserves resources, and promotes sustainable farming techniques in the scenario of evolving climate challenges.

E. PEST AND DISEASE CONTROL

SA transforms pest and disease control with innovative technologies. IoT devices and sensors continuously monitor fields, detecting early signs of pest infestations and diseases [77], [78]. Drones equipped with imaging technology provide high-resolution views, enabling precise identification of affected areas. This data is processed by ML and data analytics algorithms, predicting potential outbreaks and recommending targeted interventions [79]. Automated systems can then administer precise amounts of pesticides or deploy biological control methods. This data-driven approach in pest and disease control minimizes the chemicals used, lessens the environmental impact, and enhances overall crop health, all of which help to promote effective and sustainable farming practices in the SA era [26], [80].

F. SUPPLY CHAIN MANAGEMENT

SA optimizes supply chains by integrating IoT, blockchain, and data analytics technologies. Sensors and GPS devices monitor the movement of agricultural products at every stage, providing real-time data on location and conditions [81]. Blockchain ensures transparent and secure record-keeping, enhancing traceability and accountability. Data analytics processes this information, offering insights for efficient inventory management, transportation planning, and demand forecasting. By minimizing delays, reducing waste, and improving overall transparency, SA contributes to a more streamlined, resilient, and sustainable agricultural supply chain, meeting the demands of modern markets and ensuring the delivery of quality products to consumers [82], [83].

G. FARM MANAGEMENT

SA introduces farm management systems, integrating technologies like IoT and data analytics to streamline and enhance agricultural operations. These systems provide farmers with centralized platforms for monitoring and controlling various aspects of their farms [84]. Real-time data from sensors and devices offer awareness of soil conditions, crop health, and equipment status. Automated processes, guided by predictive analytics, optimize resource allocation, including water, fertilizers, and pesticides [85]. These intelligent systems also facilitate planning, scheduling, and decision-making, empowering farmers to enhance efficiency, minimize costs, and adopt sustainable practices for a more technologically advanced and productive farming future [20].

IV. BENEFITS AND CHALLENGES

A. BENEFITS

The world is facing multiple challenges; climate change and overpopulation are the two primary of these. Climate-smart agriculture (CSA) is a beneficial approach to tackle these issues by focusing on increasing agricultural productivity, resilience, and reducing greenhouse gas emissions [86], [87], [88]. In developing countries, small-level farms play a very crucial role in the agriculture sector. So, making them adaptive to tackle climate effects is very important. CSA mainly focuses on the farmers' benefit by helping them to have stable and higher incomes in a sustainable manner. The two most beneficial and commonly used CSA methods are water management and crop rotation. These methods can significantly reduce the adverse effects of unpredictable weather conditions. Additionally, having access to climate information services is becoming increasingly important as it helps in the realization of even basic CSA methods, like plantation and harvesting at the right times, much easier [22]. The adoption of CSA has highly benefited the farmers in Kenya to increase potato production. Potato yield increased by 61% with the use of seed management technology. This was followed by further increases of 50%, 41%, 40%, and 39% with soil nutrient management, crop improvement practices, and seed management, respectively [89]. In 2010, The Food and Agricultural Organization introduced CSA in Pakistan as an innovative and more sustainable approach in agriculture, aiming to the raise effective use of natural resources, boost adaptability, and increase agriculture productivity while also reducing greenhouse gas emissions. By implementing CSA practices and technologies, the adverse effects of climate change can be minimized on cotton products, both at the individual level and broader level. The results of this approach show several benefits, including harmonious germination, an increase in crop yields, bettered fiscal returns, and increased overall effectiveness in resource application [90].

Crop yield prediction is a very challenging task in agriculture that has significant implications at various levels, from global to local fields. In order to predict crop yield, multiple factors need to be considered, like soil quality, weather conditions, environmental factors, and specific crop characteristics. Recently, Lin et al. [91] developed a transformer-based DNN model to predict crop yields at the county level across the United States while incorporating climate factors. The implementation of PA offers many benefits, including the capacity to increase crop yields, enhance crop quality, and reduce environmental impact [92]. We may learn more about the interactions between variables such as the availability of water and nutrients, pests, diseases, and other field conditions during the growing season by modeling agricultural yields [93]. PA also acknowledges the fact that agricultural fields exhibit variations in both time and space, and it deals with these variations by gathering information, interpreting it, assessing it, and then implementing control measures. Different researchers have shown that PA is very beneficial when it comes to conserving water, energy in irrigation, and enhances profitability by ensuring the use of the right applications in different parts of farming [94].

B. CHALLENGES

Smart farming, a relatively recent concept, involves the use of information and communication technology for efficient farm management that prioritizes productivity, profitability, and the conservation of natural resources. However, the adoption of certain smart farming technologies in Brazil has faced challenges. These challenges include limited internet access in rural areas of Brazil, and the complexity of subjecting extensive data into software, which hinders analysis and interpretation. This highlights the issues with sourcing reliable information and technology features that should simplify data collection and analysis for better management. Additionally, the insufficient qualifications of the rural labor force present a significant socio-economic obstacle to the widespread adoption of smart farming technologies [95].

Embracing CSA is seen as a viable approach to ensuring food security and effectively addressing climate risks. Various CSA technologies, such as agroforestry and soil and water conservation methods like zai, half-moon, tie/contour ridges, and conservation agriculture, along with climate information services, are considered promising for adapting to climate change in West Africa. Nevertheless, challenges like a lack of clear understanding and inadequate policy and financial support hinder CSA adoption. Addressing these challenges promptly is crucial. The success of CSA in West Africa hinges on farming households and national institutions comprehending the environmental, economic, and social challenges posed by climate change and taking proactive steps to develop and implement appropriate policies.

SA is a field that leverages technology to efficiently oversee farming operations by monitoring and comprehending the ever-changing aspects of soil quality, crop growth, production, and management through creative methods. However, adopting this approach encounters several obstacles. One of the primary hurdles is the insufficient training in precision agriculture. Additionally, challenges stem from concerns related to the expenses involved, the returns on investment, and the absence of comprehensive analytics for SA data [96].

The rapid growth of IoT technology has a big impact on various industries, including agriculture. This is changing the way agriculture is done and creating new opportunities. However, there are challenges to using IoT in agriculture, such as issues with the equipment and devices, setting up the necessary networks and infrastructure, dealing with signal interference, ensuring data security, and facing organizational hurdles. These challenges are connected to the deployment of smart agricultural technology and applications [97].

The research [98] findings show that IoT components, which include both hardware and software, have made significant progress in the smart agriculture sector. Numerous advancements have been made, and IoT solutions have been deployed on extensive farms. Nonetheless, hurdles still hinder widespread IoT usage in farming. Economic efficiency and technical issues, along with policies promoting IoT integration in agriculture, are key concerns. In terms of economics, agriculture faces low profits due to inherent risks, prompting the need for a thorough cost-benefit analysis for IoT adoption in agriculture. Security and privacy are critical challenges as IoT in smart agriculture raises concerns about data and system protection from cyber threats. The limitations of IoT devices make the implementation of robust encryption algorithms challenging, leaving systems vulnerable to attacks that can compromise functionality.

Mehedi at al. [99] have identified a number of challenges of utmost importance in remote-sensing based SA. Among several, they believe that irrigation decision support systems and spectral data challenges, are the two aspects that still demand attention by the scientific community. They argue that despite the technological advancements, seamless integration of various components, such as sensors on ground, and the airborne UAV, is essential, which puts stringent efficiency requirements on the decision support systems for real-time operations.

One major challenge facing the adoption of SA worldwide, especially in the developing nations, which often gets overlooked, is the lack of regulations regarding farming practices. This usually leaves gaps in legal protection of farmers' data, which in turn raises further challenges: 1) Unauthorized access of data collected through various sensors and devices, often leads to privacy breaches. 2) Unless the farmers' themselves control and manage their data, there can be an ambiguity over its ownership. This is a rising concern in the developing countries where farmers are usually not technically trained, and therefore, data acquisition and management are often outsourced to third parties. 3) While data analytics provides valuable insights, it also raises a concern about data aggregation and usage. Refer to Amiri et al. [25], who have thoroughly discussed privacy issues in the context of SA.

V. ONLINE DATASETS

It is widely accepted that datasets serve as benchmarks for future research by allowing researchers to compare the performance of various techniques and algorithms. At the same time, the dissemination of valuable datasets allows researchers with different backgrounds and expertise to work with the same data, potentially leading to interdisciplinary insights and innovations. In what follows, we list and briefly discuss the datasets available to the public. Our selection is inspired by their number of citations, downloads, and usability:

FIGURE 9. Sub-set of images from corn dataset.

leftmargin=1em

1) *Wheat leaf rust* [100]: Wheat leaf rust, mostly found in Hebei, Shanxi, Inner Mongolia, Henan, Shandong, Guizhou, Yunnan, Heilongjiang, and Jilin, is sometimes referred to as wheat stalk rust and stripe rust. It mostly affects wheat leaves, causing sores that resemble herpes and infrequently developing in the leaf sheath and stem. There are 531 images in this dataset.
2) *Wheat leaf* [101]: This dataset is derived from the wheat crop images in Ethiopia. The crop exhibited infections caused by viruses, bacteria, and fungi. Within this study, the primary focus was on two major diseases: Stripe Rust and Septoria in wheat leaf images. The dataset comprised 102 instances of healthy leaves, 208 instances of leaves affected by stripe rust, and 97 instances of septoria-detected wheat leaves.
3) *Rice leaf disease dataset* [102]: The compiled dataset comprises 5932 images encompassing four disease types: Tungro (1308 images), Blast (1440 images), Brown spot (1600 images), and Bacterial Blight (1584 images). The dataset is accessible in the data archive of Mendeley.
4) *Corn leaf disease* [103]: This is an extensive dataset focused on classifying diseases affecting corn or maize plant leaves. It was created, utilizing data from the renowned PlantVillage and PlantDoc datasets. Throughout the dataset creation process, specific images deemed uninformative were eliminated to ensure data quality. This dataset contains 1306 Common Rust images, 574 Gray Leaf Spot images, 1146 Blight images, and 1162 healthy leaves images.
5) *Crop recommendation* [104]: The dataset enables users to develop a predictive model for suggesting

the most appropriate crops to cultivate on a specific farm, considering diverse parameters. It was created by enhancing existing datasets related to rainfall, climate, and fertilizer information, which were already accessible to India.

6) *Cauliflower* [105]: The dataset comprises a total of 656 images containing farmland scenes. Three different forms of diseases are found in each file: bacterial spot rot, black rot, and downy mildew. Furthermore, an image showcasing a disease-free cauliflower is incorporated.
7) *Cotton leaf* [106]: This dataset contains images of cotton leaf. Digital cameras were used to create the dataset, and the pictures were acquired in various fields. It contains 127 images of Cercospora, Alternaria, Grey Mildew, Bacterial Blight, and healthy leaves.
8) *Rice brown spot* [107]: This dataset contains 3494 images of Rice flax spot. The latter is prevalent in all rice-growing areas of China, posing a significant threat to rice cultivation. The disease can manifest from the early seedling phase to the later harvest stage, causing harm to the above-ground sections of rice plants, primarily focusing on the leaves. The initial symptoms involve minor brown spots, which gradually enlarge into oval-shaped lesions.
9) *Diseases of maize in the field* [108]: There are 2355 images of maize leaves with different diseases in this dataset. The dataset includes cases of the following diseases: Phaeosphaeria Leaf Spot, Southern Rust, Common Rust, Northern Corn Leaf Blight, and Grey Leaf Spot. The cases were taken at different times and places in South Africa.
10) *Maize production dynamics* [109]: This dataset contains information concerning maize cultivation within Salima District in central Malawi. The study primarily focused on the data from the 2004/05 season to the 2018/19 season. The dataset includes details about the cultivated maize acreage, actual maize production, and maize yield. Additionally, it encompasses recorded rainfall and temperature data specific to the study region. The dataset also highlights maize prices prevailing within the research area.
11) *Temporal progress of maize diseases* [110]: The dataset is intended to assess the temporal progress of four different diseases in corn: southern rust, Cercospora leaf spot, white spot, and spot blotch, as well as their correlation with climate variables. The latter includes daily temperature, humidity, rainfalls, and daily precipitation.
12) *Annotated apple leaf disease* [111]: This dataset consists of labeled pictures of apple leaves afflicted by various diseases sourced from the PlantVillage dataset. It is used for research involving image segmentation methods. The annotations are structured following the Mask RCNN annotation style. This dataset is valuable in accurately locating the affected areas on the leaves, a crucial aspect for forecasting the extent of disease severity.

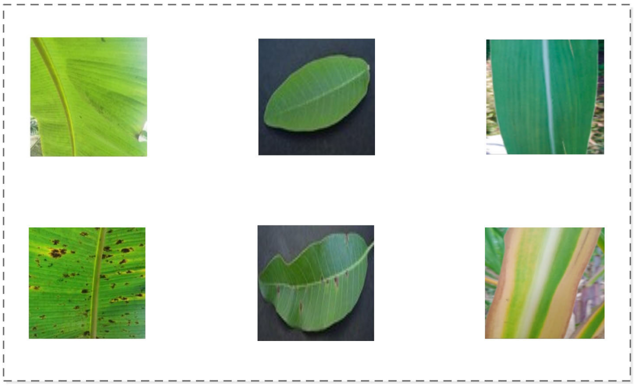

FIGURE 10. Sub-set of images from Banana & Maize Datasets.

13) *Apple tree leaf disease segmentation* [112]: This dataset includes apple leaf disease images from four different apple experimental demonstration stations at Northwest China's University of Agriculture and Forestry Science and Technology. The images were taken with a Glory V10 mobile phone, showing different disease levels. Around 51.9% were taken in a lab and 48.1% in cultivation fields, under various weather conditions and times of the day, featuring diseases like gray spot, leaf spot, rust, and brown spot.
14) *Banana leaf disease images* [113]: This is a banana plant leaf image dataset. It was collected from various parts in the south of Ethiopia, where bananas are grown extensively, and Xanthomonas wilt and Segatoka leaf spot diseases are common. Using a smartphone, images of the diseased and healthy banana tree leaves were gathered.
15) *Sugarcane leaf disease dataset* [114]: This is a Manually collected image dataset of sugarcane leaf diseases. It comprises five primary categories: Healthy, Mosaic, Redrot, Rust, and Yellow disease. These images were captured using smartphones of diverse configurations to ensure a wide range of variations. It is a balanced dataset encompassing 2569 images. The image sizes are not constant as they originate form various capturing devices; all images are in RGB format though.
16) *Diseased leaf and fruit images* [115]: The dataset comprises images of diseased winter jujube fruits and leaves gathered in their natural environment, showing common symptoms from the greenhouse winter jujube orchard in Dali County, Shaanxi province, China. These images were captured using IoT sensors at various growth phases, with an additional 100 healthy leaves and fruits included as negative samples. Overall, the dataset contains 700 images of diseased winter jujube.
17) *Mango leaf disease* [116]: The dataset comprises 4000 mango leaf images, each with dimensions of

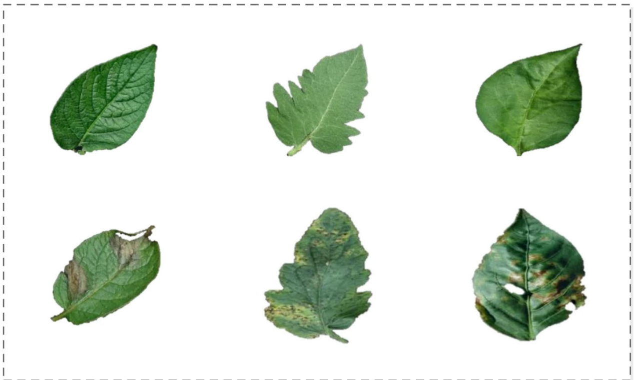

FIGURE 11. Sub-set of images from Plant village dataset.

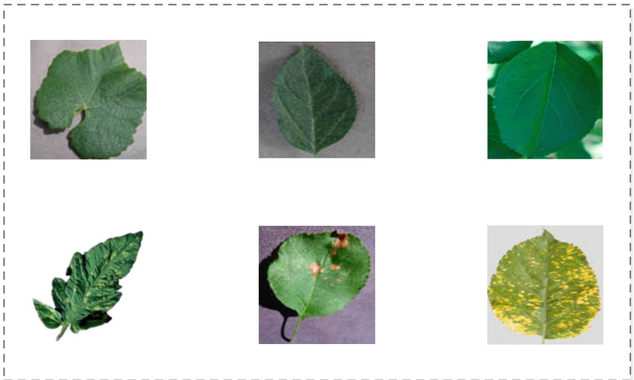

FIGURE 12. Sub-set of images from PlantifyDr Dataset.

240 × 320 pixels, presented in JPG format. Among these images, approximately 1800 showcase distinct mango leaves, while the remaining images have been generated through zooming and rotating techniques to provide variations. The dataset is categorized into eight classes, encompassing different health conditions of the mango leaves. Each of the eight classes contains 500 images, ensuring a balanced distribution of instances across the entire database.

18) *Tomato leaf disease* [117]: The dataset comprises pictures of various diseases found on tomato leaves, such as Early Blight, Tomato Mosaic Virus, Leaf Mold, Target Spot, Tomato Yellow Leaf Curl Virus, Bacterial Spot, Spider Mites, Late Blight, Two Spotted Spider Mites, Septoria Leaf Spot, and Tomato Healthy. There are 1000 images for each disease, totaling 100,000 images.
19) *Plant village* [118]: This dataset contains images of diseased plant leaves together with their labels. It was developed for use in systems that identify plant diseases. It encompasses 54,303 images of different diseases in plant leaves.
20) *Cotton plant disease* [119]: This dataset encompasses images of five major cotton plant diseases. The diseases are Army Worm, Aphids, Powdery Mildew, Bacterial Blight, and Target Spot. Furthermore, the dataset incorporates a collection of healthy leaf images, facilitating comparison with the images of diseased plants. Its primary emphasis is on diseases that exclusively affect leaves, with no inclusion of reference images of diseases occurring on stems, buds, flowers, or bolls.
21) *Corn leaf diseases (NLB)* [120]: The reason for creating this dataset was to use it with a drone to find and map diseases in Corn/Maize fields. The dataset has two main folders: one called *Healthy* for healthy plants, and the other called *Diseased (NLB)* for plants with diseases. Each folder has pictures that match its name. There are 4000 images in these two folders.
22) *Potato leaf disease detection* [121]: This dataset contains images of potato leaf. There are three files in the dataset having 2000 images. Two files have images of potato leaves with diseases Early Blight and Night Blight and another file contains healthy potato leaf images.
23) *Potato and tomato* [122]: This dataset is a smaller part of the well-known Plant Village dataset. It only focuses on two types of plants: potatoes and tomatoes. And each type has three categories: Early Blight, Late Blight, and Healthy. That makes a total of six groups. This dataset may be used to sort plants into different groups or to find a sick leaf. Pictures in the training set of this dataset were made smaller by cutting in the middle, turning a bit, and making them a bit blurry. This helped in making the dataset better for training.
24) *PlantifyDr* [123]: This is a Plant leaf disease detection image dataset. It comprises 125,000 pictures in JPG format. These pictures show 10 different kinds of plants, including apples, bell peppers, cherries, citrus fruits, corn, grapes, peaches, potatoes, strawberries, and tomatoes. Altogether, 37 different diseases can affect these plants. The pictures have been changed a bit to make them better for learning, and are amenable to further alteration if desired.
25) *Grape disease* [124]: Grape diseases result from diverse fungal, bacterial, and viral pathogens that can invade grapevines, causing decreased yield, inferior fruit quality, and sometimes, the demise of the plant itself. These diseases wield a substantial influence on the grape industry, impacting the production and quality of grapes utilized for wine, juice, and direct consumption. This dataset consists of 9027 images of grape leaves. It has four categories Black Rot, ESCA, Leaf Blight, and Healthy. Each category contains multiple images.
26) *GroundNut leaves* [125]: This dataset is used to count leaves in a given image. It is part of a complete machine learning mobile app, which finds and measures how sick groundnut plants are. The dataset contains 166 images and their corresponding labeled XML files.

27) *Corn leaf infection* [126]: This dataset comprises images of corn leaves partially infected by pests like Fall Army-worm. The dataset is divided into two categories: the first comprises 2000 healthy plant images, and the other comprises 2226 infected leaf images. A supplementary CSV file is also included that annotates the particular disease in the given image using a tool called VoTT.
28) *Crop statistics FAO - All countries* [127]: Time-series statistics are recorded for 173 crops from 474 countries (including states, provinces and other affiliated regions in case of larger countries). These are divided into different groups like main crops, fruits, and vegetables. The datasets report land-use and yield for each category along with population of the region. The goal is to gather all this data to allow for efficient forecasting of essential crops worldwide.
29) *Crop production & climate change* [128]: This dataset reports yield of wheat, maize, rice, and soybeans. They measure the amount of crops in tons for each hectare of land. This data is about crop production between 2010 and 2016 for 48 countries.
30) *Mango leaf health detection* [129]: This dataset includes pictures taken from drones that flew over mango farms and mango trees grown in backyards. There are 732 images along with their XML files.
31) *Leaf disease segmentation* [130]: In this dataset, there are 588 images of leaves with disease and 588 masks of corresponding pictures. The latter show both the background and the sick parts of the leaves. The images, which were taken from PlantDoc images, belong to leaves from Apple, Bell Pepper, Corn and Potato. This dataset may be used for disease segmentation.
32) *Rice leaf diseases* [131]: There are 120 JPG pictures of diseased rice leaves in this dataset. Based on the type of disease, the photos are categorized into three classes: bacterial leaf blight, brown spot, and leaf smut. Every class contains forty images.
33) *Rice leaves* [132]: This dataset has pictures of four different diseases that affect rice plants. The pictures are split into two groups: one for training and one for validation. Each group has pictures sorted into four types based on the category of disease: BrownSpot, Healthy, Hispa, and LeafBlast. The pictures have different sizes and shapes. This dataset has 3355 JPG image files.

Table 2 summarizes the characteristics of these datasets. Several other datasets that are not directly relevant to our study, but may be used as a reference for understanding the challenges associated with creating datasets and their usage, are also available online. One such example is by Mowla et al. [133], in which the authors have collected image samples for forest fire detection using a UAV, and highlighted several challenges in their usage. Any supervised machine learning application, be it the case of SA or not, will pose such challenges to researchers to overcome. Generally, there are four challenges that one must consider overcoming while adopting online datasets as follows:

1) Data quality and accuracy: Inconsistent, erroneous, incomplete and outdated datasets are likely to yield inaccurate predictions.
2) Standardization: Different datasets are likely to follow different standards and formats. This makes it practically difficult – if not impossible – to integrate data from multiple sources and modalities.
3) Initial cost: Being able to use online datasets often imposes a requirement for training beforehand, which is likely to incur a certain initial cost.
4) Privacy and security: Depending upon the application, privacy and security of data may become crucial for confidentiality. This is specifically true for applications related to health, defence and agriculture.

VI. SMART AGRICULTURE: RECOMMENDATIONS, INITIATIVES, AND SUCCESS STORIES

A. RECOMMENDATIONS

Agriculture plays a vital role in the economic growth. Therefore, introducing SA to rural regions will greatly benefit the farming sector. Approximately 85 percent of the global population will reside in developing nations by the year 2030. This implies that these nations require data-driven cutting-edge technology to enhance agricultural output and boost their economies. This will not only boost their GDP but will also guarantee food security for their citizens. Emerging technologies such as AI, IoT, and smart farming are seen as possible answers to narrow the gap between food demand and production. When government initiatives back them, these technologies can improve agricultural sustainability and resource efficiency, resulting in higher production yields [134]. Smart farming utilizes IoT and cutting-edge technology to improve growing conditions by integrating sensors, computers, and AI. In Thailand, it greatly assisted farmers in enhancing crop yield and quality. Certain conditions must be met for it to be effective like farmers must be prepared to utilize this technology and be open to experimentation. The research [135] discovered that farmers are more inclined to embrace smart farming when they are prepared for the technology, embrace its utilization, engage in e-learning, and receive institutional support. Therefore farmers can be prepared by utilizing online resources and providing assistance from organizations before implementing smart farming techniques involving sensors and AI.

Climate change is increasingly posing a major issue for agriculture globally. It presents a major obstacle for worldwide farming, impacting both the growth and delivery of crops. Therefore, numerous governments are investing significant funds into research for advanced agricultural practices. They are employing cutting-edge technologies

TABLE 2. Datasets description.

Dataset Name	Total Images	Classes/ Groups	Disease Type
Wheat leaf rust	531	2	Wheat leaf rust
Wheat leaf	407	3	Stripe Rust, Septoria
Rice leaf disease	5932	4	Tungro, Blast, Bacterial Blight, Brown spot
Corn leaf disease	4188	4	Common Rust, Gray Leaf Spot, Blight
Crop recommendation	-	-	-
Cauliflower	656	4	Downy mildew, Black rot, Bacterial spot
Cotton leaf	127	5	Alternaria, Bacterial Blight, Cercospora, Grey Mildew
Rice brown spot	3494	2	Rice flax spot
Diseases of maize in the field	2355	5	Phaeosphaeria Leaf Spot, Southern Rust, Common Rust, Northern Corn Leaf Blight, Grey Leaf Spot
Maize production dynamics	-	-	-
Temporal progress of maize diseases	-	4	southern rust, Cercospora leaf spot, white spot, and spot blotch
Annotated apple leaf disease	-	-	-
Apple tree leaf disease segmentation	-	4	Leaf spot, Gray spot, Brown spot, Rust
Banana leaf disease images	-	3	infection of Xanthomonas wilt and Segatoka leaf spot dis
Sugarcane leaf disease dataset	2569	5	Healthy, Mosaic, Redrot, Rust, Yellow disease
Diseased leaf and fruit images	700	2	Diseased winter jujube
Mango leaf disease	4000	8	Mango Wilt, Mango Scab, Anthracnose, Powdery Mildew, Bacterial Black Spot
Tomato leaf disease	10000	11	Early Blight, Tomato Mosaic Virus, Leaf Mold, Target Spot, Tomato Yellow Leaf Curl Virus, Bacterial Spot, Spider Mites, Late Blight, Two Spotted Spider Mites, Septoria Leaf Spot
Plant village	54303	-	Various diseases
Cotton plant disease	-	6	Army Worms, Aphids, Powdery Mildew, Bacterial Blight, Target Spot
Corn leaf diseases (NLB)	4000	2	NLB
Potato leaf disease detection	2000	3	Late Blight, Early Blight
Potato and tomato	-	6	Late Blight, Early Blight
PlantifyDr	125000	10	Various diseases (37)
Grape disease	9027	4	Black Rot, ESCA, Leaf Blight
GroundNut leaves	166	-	-
Corn leaf infection	4226	2	Fall Armyworm
Crop statistics FAO - All countries	-	173	-
Crop production & climate change	-	4	-
Mango leaf health detection	732	2	Mango Wilt, Segatoka leaf spot
Leaf disease segmentation	588	4	-
Rice leaf diseases	120	3	Leaf Smut, Brown Spot, Bacterial Leaf Blight
Rice leaves	3355	4	BrownSpot, Hispa, LeafBlast

such as AI and data analytics. In South Korea, there is a migration of people from rural areas to urban centers, resulting in a shortage of farm workers. As per [136], utilizing innovative technologies can address these problems. CSA provides another approach to improve food security and reduce poverty. In areas such as Ghana, initiatives are directed towards enhancing farmers' abilities to implement CSA techniques in various ecological regions. Factors like economic, environmental, socio-cultural, and institutional aspects contribute to shaping the adoption of CSA practices [137].

There are potential advantages of precision farming technologies, which have the ability to decrease costs and environmental impact. Yet, adoption levels in Europe have shown varying results. In Central Italy's Plain of Tarquinia, a study revealed that farmers were hesitant to embrace precision farming technologies [138]. In China, despite efforts to enhance food security at a national level, the implementation of precision technologies is not keeping pace with other advanced economies. In order to encourage more farmers to use advanced farming technologies (PFTs), policymakers and manufacturers need to ensure technology features meet farmers' needs, engage end-users in the innovation process, and offer necessary support such as knowledge, training, and consulting services [139]. Agricultural policies play a crucial role in facilitating the exchange of information and initiatives among small and large farms. The recently introduced information-centric policies aim to provide farmers with increased knowledge about agriculture, enhance their farming abilities, and offer additional expert support. When farmers possess more information, they will not perceive the adoption of new technologies as challenging [140].

In summary, advanced technologies like AI, IoT, and smart farming can help combat food shortages by boosting production and promoting sustainability. Innovative solutions such as CSA are required to address the challenges created by climate change. The precision farming techniques can help reduce environmental effects, but their adoption varies [141]. Thus cooperative efforts, a strong infrastructure, digital literacy, adoption incentives, data security, standardization, and favorable policy frameworks are all necessary for the success of SA. Stakeholders may fully utilize SA to improve resilience, sustainability, and production in the agriculture industry by implementing these suggestions.

B. SUCCESS STORIES

Climate change is becoming a major threat to food security. Farmers are unable to tackle this situation due to their limited knowledge. A financed Bicol Agri-Water Project on Climate-Smart Farmers' Field School (CFS) was introduced by USAID in Philippines with the aim of educating the farmers. This project spanned about two years covering two wet and two dry seasons in three different sites in Bicol, Philippines. Numerous farmers graduated from 14 villages − most of them were females. The CFS program conducted weekly sessions, focusing on imparting knowledge and skills related to climate change (CC) and CC adaptation (CCA) tactics. The outcomes of this endeavor were truly promising. The knowledge of the farmers on CC, CCA increased significantly, crop yield increased and the participating farmers experienced a welcome boost in their income levels. A commendable return on investment of 49 percent during the wet season and an even more impressive 55 percent during the dry season was reported. An increase in the women participation in decision-making was also observed [142].

The Precision Farming Project was started in two districts of Tamil Nadu's Dharmapuri and Krishnagiri in India in 2004-05 [143]. It commenced with a small area of 250 acres and gradually increased to 500 acres in 2005-06 and 250 acres in 2006-07. The initial budget of this project was INR 720,000 for a period of three years, and was carried out by the Tamil Nadu Agricultural University. Farmers received financial support of INR 75,000 for drip irrigation installation and another INR 40,000 for the expenses of crop production. The farmers were first hesitant to engage in this endeavor due to years of drought, the project gained momentum after the success of the first 100 farmers and the huge profits in their produce. Subsequently, more farmers registered for participation in the second and third years, mainly due to attractive 90 percent and 80 percent subsidies respectively.

The Mau Escarpment generates a shadow of rain across the Nyando basin and relies on agriculture, primarily maize, beans, and sorghum, as well as mixed livestock farming. The region experiences an annual rainfall of 1200 mm: 35 percent in the minor rainy season, which runs from October to December, and the remaining 65 percent during the main growth season running from March to May. The onset of rainfall varies, affecting the length of the growing season, and hence the land degradation adversely affects farming.

Three sizable community-based organizations–the North-East Community Development Programme (NECODEP), Friends of Katuk Odeyo (FOKO), and Kapsokale–have emerged from local communities in Nyando. These associations consist of around 50 volunteer groups from more than 100 villages, with 80 percent female members. Between 2011 and 2015, they combined their resources to create the Nyando Innovation Fund, which increased from USD 14,000 to USD 95,000. Nearly 90 percent of the local farmers sought loans from this fund, primarily for agricultural use, school fees, food, and small-scale trade activities. The community-based organizations have established smart farm (SF) demonstrations, including greenhouse farming and drip irrigation, as well as open field plots for seed multiplication. For knowledge and skill enhancement Farmers receive training through these organizations, often organized by Kenya's Agricultural Society. They have also set up input supply shops, leading to a 50 percent decrease in the use of low-quality local seeds. Additionally, climate information services (CIS) access is also provided by these organizations, which are utilized by farmers for 70 percent of on-farm decision-making [28].

The semi-arid climate of Wote, in eastern Kenya, is characterized by bimodal annual rainfall of 480-800 mm. The first rainy season, which occurs in April and May, results in short crop growth periods and significant water stress because of the uneven distribution of rainfall. In the last twenty years, around 25% of the land has been affected by erosion, mainly because of higher temperatures, increased evaporation, and occasional floods. This has negatively impacted agriculture, causing problems like pest infestations and disease outbreaks, such as Aflatoxin fungal disease, leading to significant losses in grain yields for farmers. Grain harvest has suffered particularly from aflatoxin fungal disease, leading to farmers losing up to half of their yield. Two community organizations (Kikumini-Muvau and Sinai-Kikeneani) were established in 2014 in Wote. They initially covered seven villages and grew their membership in two years from 140 to 620 households, with women comprising 70%. The CBOs created a joint fund of 39,000 USD, allowing members to borrow for agricultural investments to manage climate-related risks.

They also promote climate-smart technologies and crop diversification, with new crop varieties being cultivated by 92% of households by the end of 2015, up from 72% in 2014 [144].

Overall, the research demonstrates that CSA techniques effectively increased levels of both macronutrients and micronutrients in the soil. These techniques are advantageous for adapting to climate change across various settings, with the most significant results seen in the surface layer of soil.

VII. FUTURE TRENDS AND OUTLOOK

A. EMERGING TRENDS

In farming, new technologies are making a big difference. CSA and PA are two important ways we're improving how we grow food. These methods help us deal with problems like climate change and bad weather [145]. CSA uses modern tools to make farms better, and helps the farmers produce more food while taking care of the environment. PA, on the other hand, helps them grow more crops without using too much water or other resources [146].

Using fancy tools like sensors and drones helps farmers know more about their land. They can figure out when to water their crops and how to protect them from bugs. It's like having a better plan for planting and growing food. New technology also means less work for farmers. Machines can help with tasks like planting seeds and picking fruits. This makes farming easier and helps us get more food from the same land. It's all about making farming better and more sustainable for the future [146].

Implementing blockchain technology guarantees the food supply chain's traceability and transparency. It enables farmers and consumers to track produce from farm to table, ensuring authenticity, quality, and ethical practices. The integration of XAI, blockchain, and smart agriculture holds significant societal and economic consequences. Improved efficiency, transparency, and sustainability in the food industry could have positive impacts on farmers, consumers, and the global community [147].

Urban agriculture and vertical farming are becoming more popular as cutting-edge responses to the problems caused by urbanization and land shortages. These methods entail cultivating crops in controlled urban contexts or in layers piled vertically. Technological advancements in LED lighting, hydroponics, and aeroponics are increasing the viability and efficiency of vertical farming. In comparison to conventional farming techniques, these systems require less water and land and can yield crops all year round, enhancing food security in metropolitan settings.

The Internet of Things (IoT) is revolutionizing intelligent agriculture by integrating various systems and devices. The prevalence of smart sensors, automated irrigation systems, and tools for animal monitoring is on the rise. These devices provide continuous data streams that can be analyzed to improve decision-making processes. The advancement of 5G and low-power wide-area networks (LPWAN) is enabling real-time monitoring and control of agricultural activities, enhancing connectivity in remote areas. This interconnectedness enables farmers to easily acquire and respond to crucial information, enhancing overall farm management.

Integrating IoT devices for real-time monitoring of environmental conditions and crop health generates vast amounts of data. Data analytics assists in making decisions on this data, optimizing resources, and predicting trends. However, a framework is required to improve security and privacy in smart farms by utilizing blockchain technology's decentralized nature. The framework must securely store and manage data from IoT devices in smart farms through a distributed ledger system, ensuring data integrity and validity [148].

Robotics and automation are developing quickly, decreasing the need for physical labor and boosting operational effectiveness. Drones, autonomous harvesters, and autonomous tractors are being developed and used for planting, weeding, and harvesting. These devices provide consistent, accurate operation, which lowers labor costs and boosts production. Robotics and AI are combining to create more versatile and efficient robots that can learn and adapt to various farming settings.

To collect and analyze data on temperature, humidity, pH levels, and soil moisture, IoT gateways connect a variety of sensors and equipment. By using edge computing to process data locally, these gateways lower latency and use less bandwidth. This enables real-time analysis for immediate actions like adjusting irrigation or activating pest control. They support multiple connectivity options, ensuring reliable data transmission even from remote areas, and integrate with cloud platforms for further analysis. Additionally, IoT gateways facilitate remote monitoring and control of agricultural operations. This allows farmers to adjust systems and receive alerts remotely. They also enable automation, and security through data encryption, and support applications like precision farming, livestock monitoring, greenhouse automation, and supply chain management, enhancing efficiency, sustainability, and productivity in agriculture. IoT gateways are rapidly advancing and revolutionizing the SA.

There's a growing emphasis on sustainability and environmental impact reduction. This includes the utilization of renewable energy sources, organic farming techniques, and minimizing chemical inputs. The implementation of 5G technology facilitates more rapid and secure data transmission, crucial for real time monitoring, remote operation of machinery, and seamless connectivity in rural areas [149]. Wearable devices for livestock and plants, such as smart collars for cattle or tags for monitoring individual plant health, provide continuous data on animal behavior and crop conditions, aiding in the early detection of health issues or stress factors [150].

Cloud platforms allow the storage, processing, and analysis of large quantities of data gathered from IoT devices and sensors. These platforms offer flexible options for analyzing data in real-time and monitoring activities. This enables farmers to make educated choices regarding crop management, irrigation, and pest control. Cloud platforms improve operational efficiency and resource optimization by providing remote access to data and automation features. Additionally, they aid in incorporating advanced technologies like AI and machine learning, which result in predictive insights and enhanced farming techniques. In the end, cloud platforms help boost productivity, sustainability, and resilience in contemporary agriculture.

The progress in biotechnology and genetic engineering, such as gene editing, is improving crop resilience, creating drought or disease-resistant types, and enhancing nutritional value [151]. These developments are aimed at transforming agricultural methods to be more effective, eco-friendly, and able to cope with growing worldwide food needs while reducing environmental harm.

To ensure smooth data exchange between different devices and systems, communication protocols are essential in smart agriculture. These protocols like MQTT, Zigbee, LoRaWAN, and NB-IoT help in ensuring the dependable and effective transmission of data from sensors and IoT devices to central servers or cloud platforms. These protocols enable precision farming practices, enhance resource management, and improve agricultural productivity through real-time monitoring and control. The selection of protocol is based on factors such as range, power usage, and data rate needs, guaranteeing top-notch connectivity and efficiency in various agricultural settings. These protocols are developing very fast and are transforming the SA.

B. POTENTIAL IN DEVELOPING COUNTRIES

SA is really helpful in countries that are still growing. It helps fix problems and makes farming better. This kind of farming makes things work better by using resources well, so farmers can grow more food. This is super important in places where there isn't a lot of stuff to use, and where the weather is changing a lot. Smart farming also helps farmers get the info they need. They can use apps on their phones or look things up online to learn about farming [152]. This helps them make smart choices about what to do on their farms. Plus, it's easier for them to sell their crops and get fair prices because they can use websites and apps to connect with buyers. And they can get money and insurance more easily too.

SA also helps farmers deal with changes in the weather. There are cool tools that help them use less water and know when bad weather might be coming. This way, they can be ready and keep their crops safe. Plus, smart farming creates more jobs in places where people live and work on farms. These new ideas help farmers use their resources better, make less waste, and grow more crops [153].

In underdeveloped countries, technology can help small farmers improve their farms, leading to greater efficiency, higher crop production, and increased sale prices. SA helps improve crop yields and prevent pests and diseases to ensure food security. Advances in biotechnology for crop production can also improve food quality, especially in areas with limited access to nutritious food [154].

Governments and support organizations are investing in smart farming to help farmers adopt these new technologies, offering discounted tools, training, and improved access to assistance. Smart farming practices also promote environmental sustainability by reducing chemical use, promoting soil health, and efficient water usage [155]. By incorporating these technologies, developing countries can enhance agricultural productivity, bridging the gap with wealthier nations and ensuring food security for everyone [156].

C. RESEARCH DIRECTIONS

Changes in SA research aims to improve farming by creating more efficient sensors to collect diverse information about soil, crops, insects, and weather. Scientists are enhancing sensors to be more affordable and versatile in data collection, along with advancing computer capabilities for better data analysis and predictions. Additionally, researchers are utilizing big data tools to assist farmers in crop management, disease detection, and yield forecasting, while also focusing on ensuring seamless communication and energy efficiency among various farm devices for integrated functioning.

Developing robust networks and protocols suitable for remote and rural areas is essential. Continued research is required on adaptable and cost-effective robotic systems for various farming tasks, like planting, harvesting, and precision spraying. Advancements in AI will assist in autonomous navigation and manipulation. Developing technologies in agriculture, such as precision irrigation systems, drought-tolerant crops, and weather prediction models, to aid with climate change adaptation. Exploration of blockchain technology is essential in agriculture for transparent and secure data sharing across the supply chain. Research in scalability, interoperability, and real-time traceability of agricultural products is also needed [157].

The research focus is on creating energy-efficient systems and renewable energy sources for smart agriculture to reduce dependence on fossil fuels and cut operational costs [158]. Progress in biosensors for early disease, pest, and nutrient deficiency detection in crops, along with biotechnological methods for genetically modified crops with improved characteristics. Research works are in progress on developing user-friendly farm management software. It integrates different data sources to offer farmers actionable insights for better decision-making and resource management [159]. The latest research investigates the social and economic effects of smart agriculture on rural communities, including factors like accessibility, affordability, and technology adoption by small-scale farmers [160], [161]. Research and discussions exploring creating appropriate regulatory frameworks and policies are also required. This will encourage innovation, protect data privacy, and promote widespread adoption of smart agriculture while considering ethical concerns [162], [163].

Working together is really important for making research better and putting smart farming ideas into action. This means scientists, tech experts, farmers, people who make rules, and others all need to work together.

VIII. KEY FINDINGS AND CONCLUSION

Smart farming has made significant advancements, revolutionizing agricultural practices with the help of smart devices, AI, robots, and data in the past decade. Leveraging from these advancements, certain developing countries have taken an initiative to adopt smart agricultural practices, and have subsequently reported their findings, which deserve to be recognized at an international level. In the following, we summarize the key findings of our humble effort in collecting several such works, which have individually contributed towards the development and/or promotion of smart agriculture framework and practices.

1) Several innovative technologies, such as sensors and drones for real-time monitoring of soil, weather, and crop conditions, AI and machine learning algorithms for predictive analytics, crop disease detection, and yield prediction, and blockchain for ensuring transparency and traceability in the supply chain, greatly improve the smart farming practices. This in turn allows farmers to optimize resources and make informed decisions.
2) Optimizing inputs like water, fertilizers, and pesticides demonstrate enhanced productivity. At the same time, use of robots for planting, harvesting, and weeding ensure environmentally friendly farming practices, such as reducing chemical usage to preserve nature while ensuring ample food production. Efficient water usage based on real-time data allows for water conservation.
3) Availability of open access online datasets for soil health, weather patterns, and crop yields encourage domestics farmers contribute their own data to improve models and predictions, and be an active part of the ecosystem.
4) Rural economies witness jobs creation, improving infrastructure, and increasing market and financial access. Technology is developed to help farmers adapt to climate change by offering resilient crops, water management solutions, and predictive tools for extreme weather. The data gathered drives innovation, from AI predictive models to tailored farming solutions.
5) The inclusion of SA by small-scale farmers in developing regions is hindered by affordability, connectivity issues, and lack of training. Concerns surrounding privacy, security, and ownership arise during the gathering and sharing of large amounts of agricultural data, leading to the need for strong data protection measures. Inadequate infrastructure and poor connectivity in remote or underdeveloped areas impede the effective use of smart agriculture technologies. The technological gap between large commercial farms and small-scale farmers widens, hindering the potential benefits of smart agriculture.
6) Developing appropriate regulations and policies that promote innovation and address ethical, legal, and social implications is essential.
7) Overall, while SA can potentially revolutionize the agricultural sector, overcoming challenges related to accessibility, data security, and policy frameworks is necessary for its full potential to be realized. Collaboration among stakeholders, continuous research and development, and a focus on inclusion is vital to ensure that smart agriculture benefits all farmers, enhances global food security, and encourages sustainable agricultural practices.

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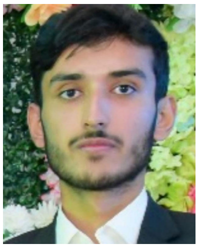

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