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An Overview of IoT Solutions in Climate Smart Agriculture for Food Security in Sub Saharan Africa: Challenges and Prospects

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Abstract

INTRODUCTION: Climate smart agriculture (CSA) which involves the integration of IoT and cloud computing is an emerging agricultural paradigm that is foreseen to be the main driver of agriculture as the 21st century progresses. Sub-Saharan Africa lags in this regard and therefore deserves a special focus.
OBJECTIVES: This paper presents an overview of Internet-of-Things (IoT) solutions in CSA in the context of food security in sub-Saharan Africa (SSA)
METHODS: An overview of the status of food insecurity in SSA and associated factors is presented. The paper then focused on IoT as a technology and how it can be used for CSA in SSA through use cases; possible challenges were also examined.
RESULTS: The paper showed that with CSA, SSA can become a net exporter of food.
CONCLUSION: The paper concludes with open issues like the funding of research and development which must be addressed if SSA is to leverage IoT technology to attain food security.

Keywords: Climate Smart Agriculture, Sub Saharan Africa, Internet of Things, Food Security

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1. Introduction

The projected rapid growth in the continent of Africa has made agriculture one of the most critical components in the economics of nation-states that aspire to attain an acceptable level of food security and food sufficiency. According to a UN report on world population prospects (1), and the report by the Food and Agricultural Organization (2), Africa's population will be much higher than the one billion mark by 2050. This exponential increase in population alongside the simultaneous transition in technology, socio-economic policies, rural-urban migration, and infrastructure will continue to have implications for sustainable agriculture if food security is to be achieved. In the light of this changing reality, sub-Saharan Africa (SSA) in particular must make a fundamental paradigm shift in the practice of agriculture through the involvement of technology that is reliable, robust, and affordable. This brings in the notion of climate smart agriculture (CSA) which is the integration of agriculture with cloud computing, mobile broadband technologies, and Internet-of-Things (IoT) to make agriculture less vulnerable to climate change, and sustainably produce sufficient food.

At the heart of this integration is an agricultural practice that can monitor, predict, and control environmental parameters like soil moisture, humidity, wind speed, and the amount of sunlight which when properly harnessed guarantees a very high yield. To successfully make accurate predictions and estimations of these factors, large volumes of data must be collected and processed over time to discover hidden patterns of changes in these factors. The

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collection of these data over time generates a large amount of data which could be in petabytes $\left(10^{15} bytes\right)$ or exabytes $\left(10^{18} bytes\right)$. As a result of this, big data analytics becomes inevitable and an integral part of the CSA scheme that is driven by IoT and cloud computing to yield a high volume of production. To this end, vast computational processing power and storage infrastructure must be available if the huge amount of data generated from CSA is to be processed in a stipulated time and decisions made to meet critical deadlines. However, the cost implication of such infrastructure is prohibitive for developing regions like SSA whose farmers barely have access to credit. Fortunately, cloud computing and IoT are mitigating this challenge by making available powerful computer systems with large processing power and large data centers which can store vast amounts of data for big data analytics at a fraction of the price that it would cost to set up these infrastructures. The only challenge will be learning and utilizing the cloud access technology as it applies to agriculture to address the problem of food insecurity in SSA.

This paper presents an overview of the problem of food insecurity in SSA with its aggravating factors. The paper looks at the role of trade and post-harvest activities and how they impact SSA's drive to achieve food sufficiency. The paper also examines CSA and its associated technologies of cloud computing, IoT, and Big data analytics and how this new paradigm can be applied to revolutionize agricultural production in SSA. Hence, the paper is organized as follows: Section 2 looks at the status of food insecurity in SSA and the aggravating factors; section 3 examines CSA and how IoT is playing a central role in making it a reality. Section 4 presents the application of IoT in agriculture within the context of the types of data measured by IoT devices and use cases; the section also reviews irrigation with IoT devices which yields better results than traditional irrigation. Section 5 looks at the challenges associated with the application of IoT and cloud computing in SSA, its possible solutions, and open issues.

2. Food Insecurity Status in Sub Saharan Africa and Aggravating Factors

Food security as defined by the 1996 world food summit organized by the food and agriculture organization (FAO) of the United Nations (UN) is a situation where all people irrespective of time and geographic location have physical, social, and economic access to sufficient, safe and nutritious foods that meets their dietary needs and food preferences for a healthy life (3). Food security is composed of four components i.e. food availability, food access, utilization, and stability (4). Food availability deals with the availability of food in sufficient quantity and quality; food access is the ability of people to acquire appropriate foods in the context of nutritious diets through adequate resources within the community in which they live; food utilization deals with the ability to utilize food through adequate diet, clean water, sanitation, and health care to reach a state of nutritional well-being which meets all physiological needs; stability is when a population have access to adequate food at all times (4). For these four components to be fully satisfied, a lot of objectives must be met. The challenges associated with meeting the objectives that will guarantee food security varies from one region of the world to another owing to differences in weather, climatic conditions, and other natural factors. However, proper utilization of modern technologies such as IoT, broadband, cloud computing, Big Data Analytics and AI will go a long way to providing optimal solutions.

In this section of the paper, attention will be focused on sub-Saharan Africa (SSA) as a region where we will discuss the factors that have made it very challenging for SSA to meet all the four components of food security despite the abundance of arable lands and favorable climatic conditions as shown in Fig. 1(5), which shows that temperature changes in SSA have been minimal for almost 60 years; this failure has made SSA an "insecure global region" in terms of food insecurity as shown in Fig. 2(6) which shows that moderate and severe food insecurity is very prevalent.

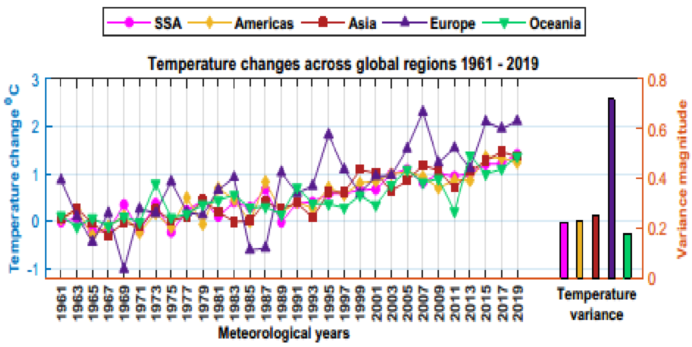

Figure 1. Global temperature changes from 1961 to 2019

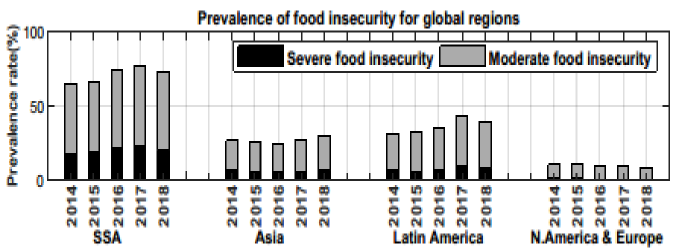

Figure 2. The global prevalence of food insecurity from 2014 to 2018

Numerous research articles have been published by agricultural scientists on the current status of food security in SSA; a common denominator to all research findings in literature is that the major persistent issues that have been exacerbating food insecurity in SSA include lack of access to modern technologies like Broadband, IoT, Cloud computing, Artificial Intelligence (AI), and Big Data Analytics (7).

Broadband internet technologies are vital in establishing automated agricultural processes, especially irrigation so that high yield can be achieved through optimal utilization of resources with minimal environmental impact (8).

IoT is a key enabling technology in climate smart agriculture (CSA), as it provides a mechanism by which remote control of farm equipment and devices with remote monitoring and data acquisition from farms can be achieved. This reduces the operating costs of running modern farms and also reduces the carbon footprint of farm machinery associated with logistics (9,10).

Cloud computing provides a platform where remote and intensive computing can be performed at a cheap rate (11). Considering that SSA has the highest poverty rate in the world (12,13), cloud computing has a central role to play to make computing services and systems affordable in SSA; this reality has a direct effect on the productivity of farmers in SSA, especially when farms are connected to IoT Platforms.

AI provides a means by which accurate predictions can be made on environmental factors which directly impact the level of productivity in agriculture; this is achieved through mining Big data to establish patterns. The availability of AI systems to farmers in SSA has the potential to reduce losses by SSA farmers as accurate and guided decisions are likely to always be made (14,15).

Big data is a revolutionary computing paradigm where rapidly changing data are collected over time and analyzed to establish hidden patterns in observed phenomena. This has the potential to aid in achieving better performance by farmers in SSA as the large volume of data collected in farming processes by SSA farmers can be analyzed to establish areas of strength and weaknesses so that proper allocation of resources can be made (16,17).

Timely input intervention is a critical factor that is central to the success of any agricultural output, and IoT aided with broadband internet access has a central role to play. A typical scenario is when soil data such as nutrients and moisture are acquired by sensors and IoT devices and sent to the internet for analysis; the outcome of the analysis typically prompts the optimal application of required nutrients. Naturally, over-and under-application of farm inputs impact negatively on outputs. Without the aid of digital technology, it is difficult to always gauge the optimal input. The use of various sensors via IoT enables real-time data acquisition, analysis, and controlled application of farm inputs.

A major advantage of timely input intervention via IoT is that farmers can maximize profit due to high yields and also breed a large amount of livestock because of the abundance of animal feeds derivable from high yields. On the other hand, if timely and optimal input interventions like fertilizers to meet soil nutrient requirements are not met, low productivity occurs which can also harm the production of animal feeds which in turn causes a depleted capacity in the breeding of livestock like chickens and pigs as shown in Fig. 3(18); the value for cattle is referenced from the left y-axis, and other livestock are referenced from the right y-axis.

The lack of technical know-how among SSA farmers on modern irrigation systems using IoT and broadband internet has resulted in significant underdevelopment of Sahelian water basins with only 20% of their irrigation potential realized (19). As a result of this, farmers have been deprived of the impressive rate of return in irrigation as a business; analysis shows that the rate of return in large-scale irrigation ranges from up to 12% in central Africa and 33% for small-scale irrigation in the Sahel (20).

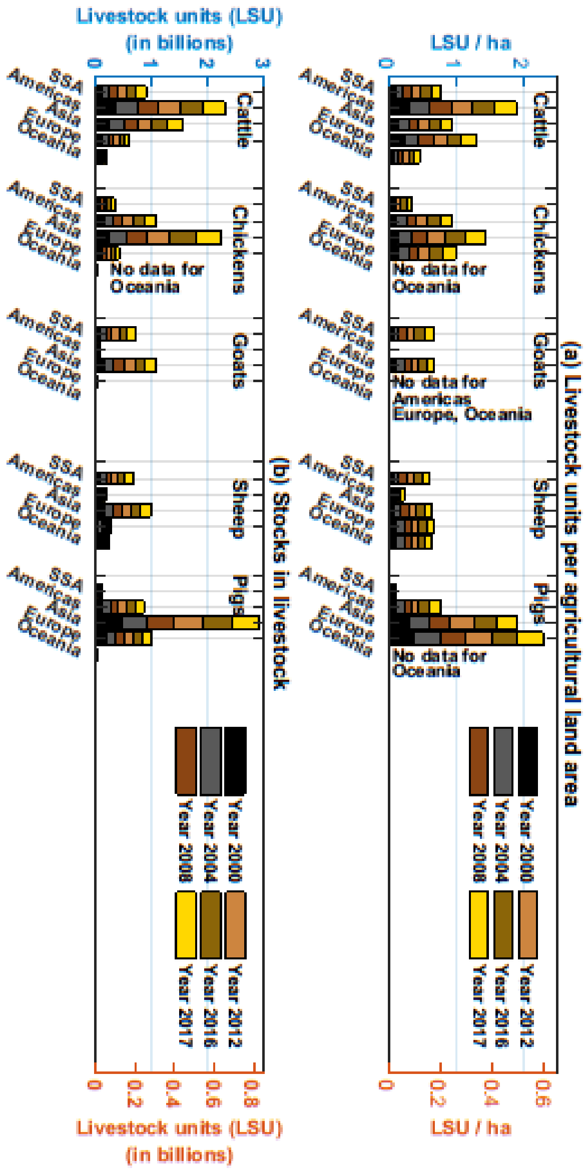

Figure 3. Livestock patterns across global regions from 2000 to 2017

3. Climate Smart Agriculture

Climate Smart Agriculture (CSA) can be defined as an integration farming technique by which agricultural resources and products including croplands, forests, livestock, crops, and fisheries are managed efficiently in a systematic procedure that mitigates the interlinked challenges of climate change and food security (26–32). It can also be defined as the approach by which agricultural strategies can be developed to guarantee food security under a changing climate (27). Accordingly, CSA aims to achieve the objectives of increasing productivity and incomes sustainably, making agriculture adaptive to the changing climate, and where possible reducing the emissions of greenhouse gases (27). To realize these objectives, CSA is divided into four important components which include(27):

- The management of crops, farms, livestock and aquaculture to achieve a near-term balance in food security and livelihoods.
- The management of landscapes and ecosystems to preserve ecosystem services that are critical for agricultural development, food security, adaptation, and mitigation.
- Enable better farm and land management by providing services on climate impacts and mitigation actions to managers of these resources.
- Enhancing the derivable benefits of CSA through demand-side measures and value chain interventions.

To achieve these four components, agriculture in SSA must transform to meet the dual challenges of climate change and population growth; this is important as Africa has the highest rate of global population growth as shown in Fig. 4. Having 60% of the world's uncultivated arable land (33) which is quite suitable for the production of crops, SSA has the potential to improve productivity through CSA and become a net exporter of food. This will entail the adoption and enhancement of CSA approaches and practices to guarantee better production systems and farmers' confidence through policies and concrete actions. For this paper, the first and third components are tangential, and one effective way they can be achieved is the deployment of the digital technologies in agriculture which comprise IoT, broadband technologies, cloud computing, Big data analytics, and AI.

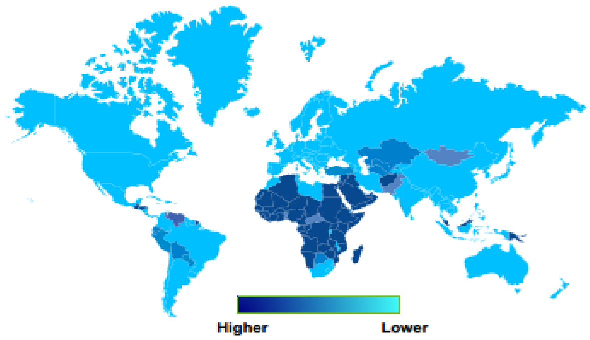

Figure 4. The global annual rate of population change 2010 – 2019

3.1. Internet-of-Things Technology

IoT can be defined as the internet connection of physical devices and systems which are actively involved in the collection and the sharing of data. Cheap processors and wireless networks have been the key enablers of this emerging technology. As of 2017, 20.35 billion devices were actively involved in IoT (34), and these devices are being used in the development of intelligent transportation, agricultural, environmental protection, positioning, and public safety systems. Devices involved in IoT are interconnected to each other and the internet through communication techniques like RFID, GPS, infrared, and wireless sensor networks (35). The connection with the internet makes it possible to perform cloud computing on the vast amount of data generated by IoT devices. The conceptual connection between IoT devices to each other and the internet is shown in Fig. 5.

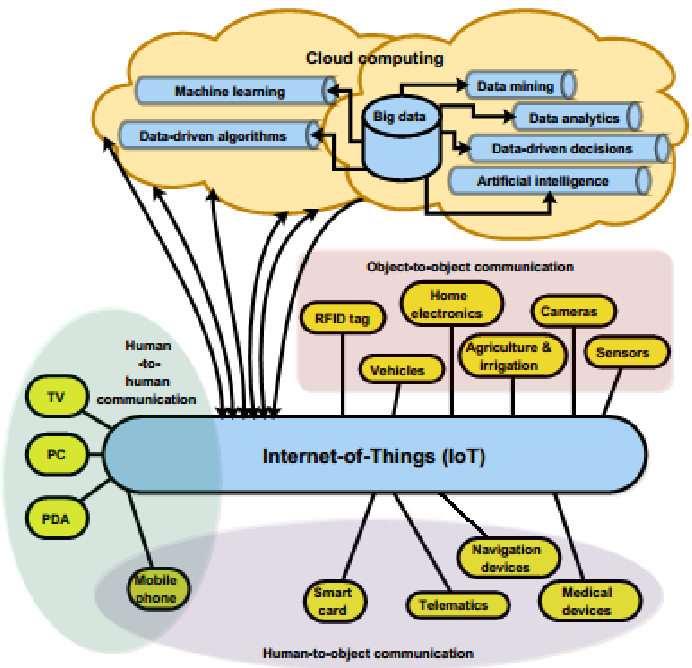

Figure 5. IoT interconnectivity and cloud computing

In literature, three main forces have been identified as the main drivers behind the strong emergence of IoT as an indispensable technology of the future; these include people, society, and businesses (36). From the perspective of people, the end-users of IoT are always in search of new things and new ways of doing things which leads to a busy lifestyle that is constantly impacted by digital technologies. Hence, new applications will have to be continuously developed to meet the demands of future lifestyles. Food security, affordable and reliable health services, and personal safety are among the key demands from a people's perspective concerning IoT. From the perspective of society, the interconnectivity provided by IoT technologies will lead to better and more efficient management of scarce resources. Data generated from IoT technology and analyzed by professionals will guarantee the formulation of policies and the setting of agendas that are grounded in contemporary reality by government agencies and legislative bodies for the benefit of sustainable societies. From the perspective of businesses, IoT will improve the efficiency of operational processes thereby bringing down the cost of doing business and increasing the competitiveness of businesses. Also, IoT will enable data-driven decisions by managers of enterprises and institutions, which in turn will reduce risks that lead to losses in business.

One of the desirable features an IoT system must possess is a seamless operation of all its components. To achieve this, utmost attention must be given to the IoT by designing a comprehensive architecture that will guarantee smooth communication between IoT components and the cloud as depicted in Fig. 5. Two well-known architectures in literature are service-oriented architecture (SOA) and application programming interface (API) oriented architecture (37). The following subsections will present an overview of these architectures as well as an overview of the technology associated with communication and sensing in IoT technology which includes radio frequency identification (RFID), wireless sensor network (WSN), middleware, near field communication (NFC), machine to machine (M2M) communication, vehicle to vehicle (V2V) communication. The following subsections will give an overview of these technologies.

3.2. Service-Oriented Architecture (SOA)

The SOA architecture is made of different subsystems which are not tightly coupled to ensure future reusability and compartmentalized maintenance. The arrangement of the subsystems as shown in Fig. 6a(38) ensures that in the event of a component failure, the other parts of the system will function as expected. This is very important if minimal downtime is to be maintained. Due to the robust structure of its abstraction and the immense benefits of the modular approach inherent in its structure, SOA has been extensively applied in wireless sensor networks, and its deployment in IoT enhances scalability and interoperability between IoT objects. The heterogeneous nature of IoT where the accomplishment of different tasks is predicated on different services in multiple geographic locations makes SOA an ideal architecture because SOA allows the building of different functions and services which are remote from each other but can be accessed through service composition.

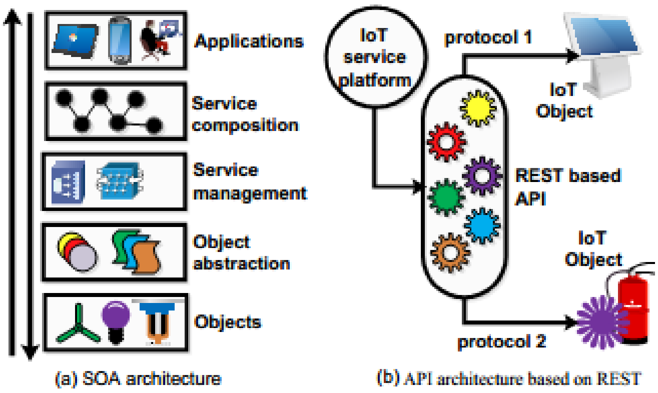

Figure 6. Types of IoT architectures

The SOA architecture as shown in Fig. 6a has five layers. The topmost layer is applications, which makes all system functionality available to the client user. This is achieved through the use of web services and applications. The service composition layer brings together the functions offered by different network objects to achieve a specific service function. Services are the only visible entities in this layer. The service management layer is responsible for ensuring that all necessary functions are made available for all objects involved in the management of resources in IoT. Typical services include status monitoring, service configuration, and dynamic discovery of objects. On a demand basis, the system management layer also performs remote deployment of new services to meet the requirements of applications. The object abstraction layer provides a mechanism by which all objects in the IoT can be communicated seamlessly. This is done by harmonizing the access to different devices using a common language and procedure. Embedding TCP/IP stacks in devices have been proposed in the literature (39); these include TinyTCP, IwIP, and mIP. These stacks provide a socket-like mechanism for interfacing with embedded applications. Object abstraction is then achieved through the integration of embedded web servers in the objects. The final layer is the objects which are networked together in the IoT scheme.

3.3. Application Programming Interface (API) – Oriented Architecture

The API architectures based on Representational State Transfer (REST)-based methods were developed as an alternative to SOA and remote method invocation (RMI) schemes, and their major requirements are network bandwidth, computational capacity, and storage capacity. This architecture is well-suited for building IoT applications that connect to physical systems and devices differently. Consider a typical scenario as shown in Fig. 6b(40) in which two different IoT objects with different protocols are connected to the same IoT service platform through the API architecture based on REST. The REST-based API takes care of the different communication protocols from IoT objects making the job of the IoT service platform easier. As a result of this, the API architecture based on REST enables service providers to focus on the functionality and the performance of their products and services rather than presentation. This architecture also allows multitenancy because it offers efficient service monitoring and tools for pricing which are better than service-oriented approaches (37).

3.4. Radio Frequency Identification (RFID)

RFID is an electronic tag equipped with a microchip and an antenna. It is usually tagged to a real-world object for tracking and identification. It uses radio waves in sending information about an object in the form of a serial number attached to the tag. The RFID performs limited tasks which are only identification and tracking, and the frequency range of its operation is limited (41). In an IoT scenario, RFID can be used to assign unique digital identities to IoT objects participating in the network so that the data being generated can be uniquely identified to a particular IoT object. This is very important in data-driven decisions when big data analytics are performed on a large set of data from different sources. Fig. 7(36) shows the working principle of the RFID.

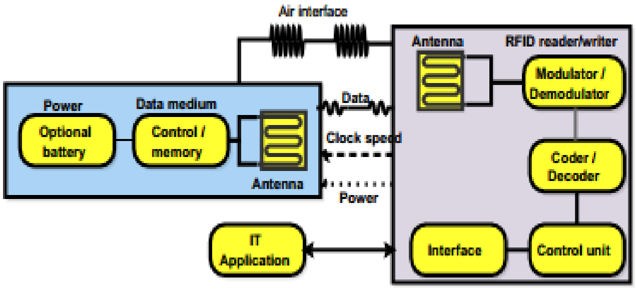

Figure 7. Working principle of RFID

3.5. Wireless Sensor Network (WSN)

WSN can be defined as a network of embedded devices called sensors that monitor and control an environment and also perform wireless communication in an ad hoc configuration. The sensors in a WSN are usually distributed spatially as autonomous sensors and can be equipped with RFID tags for better identification and tracking (42–46). WSNs usually generated a large amount of data that aids data-driven decisions in important fields like agriculture, healthcare, defense, and environmental services. A particularly important feature of WSN is its ability to send data in real-time. This is very important in systems where preventive maintenance is critical; in agricultural irrigation, for example, the maintenance of soil moisture level is important if a high yield is to be achieved, hence, using WSN to monitor the water supply system will prevent excessive downtime in water supply because the status of equipment is constantly being monitored, and this makes it possible to conduct preventive maintenance at the right time. Fig. 8a(45) shows a typical WSN and how real data can be obtained from it.

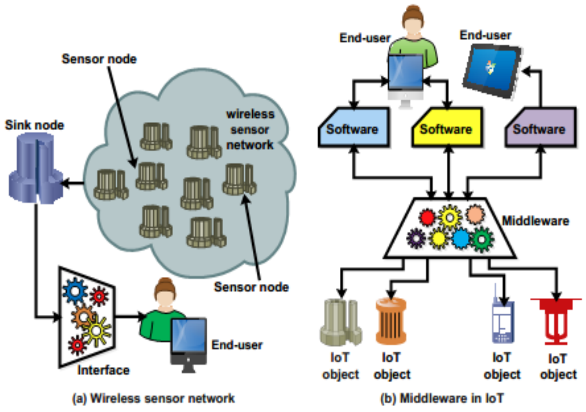

Figure 8. A typical WSN and Role of Middleware in IoT

3.6. Middleware

The middleware is software that operates between different software applications with the sole aim of making it easier for writers of device drivers to perform all the necessary input/output when writing software applications for devices. Middleware is indispensable in an IoT system because of the large number of heterogeneous devices participating in the network. The main role played by middleware in IoT is the abstraction of functional and communication capabilities of the devices involved in IoT. The abstraction includes storage, and processing of data since IoT devices are usually characterized by limited storage and low processing power (47–52). A typical middleware is a global sensor network (GSN) which is an open-source middleware sensor platform that enables the deployment of sensor devices with minimal programming effort (35). Fig. 8b shows how the middleware makes it easy to develop software applications for the end-users in an IoT network.

3.7. Near Field Communication (NFC)

NFC is a short-range wireless communication system that provides a safe and convenient way of communication between electronic devices. It operates based on RFID technology, and its frequency of operation is 13.56MHz with a maximum data transfer rate of 424kbps. In an IoT network where eavesdropping can be a security risk, NFC comes in handy because its short transmission range of 4cm prevents eavesdropping. NFC exchanges data based on the ISO 14443 A, MIFARE, and FeliCa standards, and it requires no configuration for session initiation for sharing of data. This is ideal in IoT when excessive overhead can be a challenge since most IoT objects have low memory. An important feature of NFC devices is their ability to emulate transponders by reading them (53–56). In communication, two classes of NFC devices are involved: devices that have computing capabilities and an active power supply, and devices having passive tags and are powered separately (56).

3.8. Machine-to-Machine Communication (M2M)

M2M communication is a situation where multiple electronic systems perform autonomous communication without human intervention. It is a form of communication that is fast becoming ubiquitous because of the expansion in the number of wireless communication devices and the increase in the complexity and power of software systems. Owing to its autonomous mode of operation, M2M is making major inroads into the world of IoT as more research is being made to make IoT networks as smart and efficient as possible. M2M makes it possible to develop applications that optimally monitor and manage smart buildings, healthcare services, smart irrigation in agriculture, smart transport systems, and public safety (57–62).

Based on the spectrum of operation, M2M communications are broadly classified into cellular M2M communications and capillary M2M communications (59). The cellular M2M communications are based on standards that use the resources of the LTE-A licensed spectrum, while the capillary M2M communications operate in the unlicensed ISM bands like Wi-Fi (59). Fig. 9a(58) and 9b(63) respectively show the cellular M2M communications and capillary M2M communications concepts.

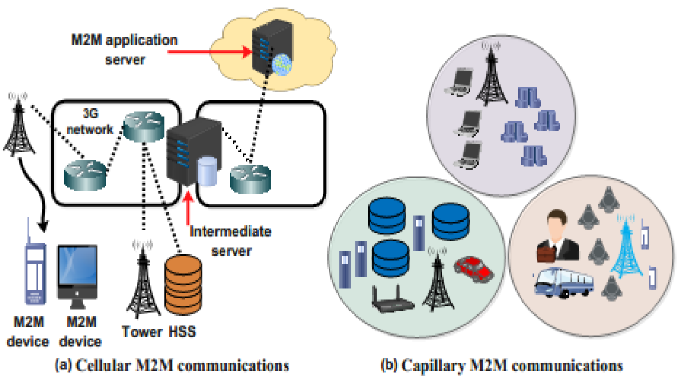

Figure 9. Types of M2M communications concept

3.9. Vehicle-to-Vehicle Communication (V2V)

V2V communication is one of the basic communication types in vehicular ad hoc networks (VANET), and it plays a central role in autonomous driving systems. However, because V2V communication is not tangential to the focus of this paper, attention will not be given to it beyond this point. The reader can refer to (64–66) for more information on V2V communication.

Having looked at IoT with its architectures and underlying technology, attention will now be focused on the application of IoT in agriculture to see how improvement in crop and livestock production can be attained with minimal impact on the environment.

4. Application of IoT in Agriculture

IoT in agriculture involves the integration of sensors, information, and communication technology (ICT) driven machinery and equipment into the entire agricultural production process from planting to harvest, processing, and storage; with this transformation, cloud computing, robotics, and artificial intelligence (CCRAI) is central, and data upon which CCRAI operates and make decisions are primarily generated by IoT devices (67–70). Key features in the application of IoT in agriculture are data transmission, data processing, data analysis, and data-driven decisions. This approach makes it possible for resources to be managed efficiently while at the same time guaranteeing the large production of food owing to the use of data analytics which has transformed agriculture from an input-intensive activity to a knowledge-intensive activity.

In this paper, we take the approach that the application of IoT in agriculture can be divided into four use cases as shown in Fig. 10. The types of sensors that can be used in the four use cases are shown in Table 1 (71), while Table 2 shows the types of data that are measured by the sensors (68).

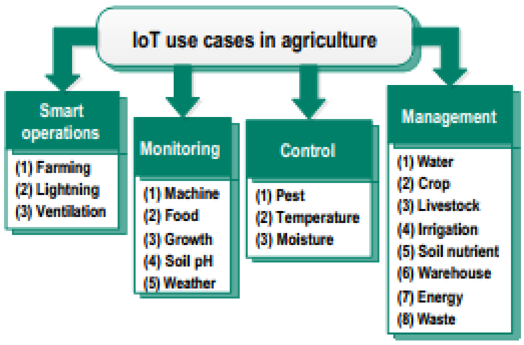

Figure 10. Use cases for the application of IoT in agriculture

Table 1. Types of sensors for IoT application in agriculture

Category	Functional description
Temperature sensors	Monitoring temperature variation in the environment of interest.
Location Sensors	These sensors measure the geographical position of any object within the area of interest. They rely on GPS for effective functionality.
Electro-Chemical Sensors	These sensors measure the chemical data of soils by detecting specific ions in the soil. The data they provide is used in determining the pH and soil nutrient levels.
Optical Sensors	These sensors are used in determining the amount of light within an environment. From the data obtained, decisions are made either to increase or decrease the intensity of light.
Mechanical Sensors	These sensors measure the mechanical resistance of the soil.
Motion sensors	They are used in monitoring the movement of mechanical parts in machinery. The data obtained is used in determining how fast machines operate in specific farming processes.
Dielectric Soil Moisture Sensors	These sensors enable the control of soil moisture levels by determining the dielectric constant of the soil being monitored.
Air Flow Sensors	The permeability of air is measured with these sensors, and they are usually operated in a fixed position or mobile mode.
Water sensors	Measures water levels in crop farming and aquaculture.
Climate sensors	Measures atmospheric parameters like wind speed, direction, and humidity to determine the condition of weather.
Plant growth sensors	Monitors the growth of plants by determining the wellness and size of leaves periodically
Livestock sensors	Provides data about the state of livestock. These data can be used in determining the optimum time for activities like milking cows.

Table 2. Types of data measured by agriculture sensors

S/N	Measured data type	S/N	Measured data type
1	Environment temperature	15	Wetness of leaf
2	Environment humidity	16	Evaporation level
3	Soil moisture	17	The volume of milk production
4	Soil pH	18	Effective fertilizer utilization
5	Water level	19	Health of plant
6	Light intensity	20	Electrical conductivity
7	Volume of CO_2	21	Solar radiation
8	Volume of rain	22	Fertility of soil
9	Wind direction & speed	23	Weight of animal
10	Soil nutrient	24	The volume of O_2 flow
11	Soil temperature	25	Livestock size
12	Level of soil	26	Livestock health
13	Humidity of soil	27	Livestock activity
14	Pressure of air		

In SSA, using the types of sensors in Table 1 and measured data in Table 2, food production and processing can be significantly improved upon to meet international standards in safety and quality. This can be achieved by using IoT as a solution in monitoring soil pH, nutrients, and toxins optimally to ensure they are maintained within acceptable limits of safety and consumption and exports. Hence, the acceptability of cash crop exports from SSA will improve, which will in turn reduce the current trade imbalance.

Using livestock sensors an IoT solution can be used in tracking the movement of livestock to mitigate the problem of cattle rustling which is rife in SSA. Secondly, using IoT solutions, the detection of disease outbreaks can be made much earlier so that effective quarantine measures can be taken.

The application of the IoT solution in Figure 23 has the potential to address the trio challenges of political disputes over natural resources, agricultural productivity, and the agriculture value chain. This is especially important due to the potential political disputes which exist over natural resources because of the critical nexus between food, water, and energy. A noteworthy reality is a current drive by SSA countries to meet the ever-increasing demand (72) for energy through dam construction for electricity at the expense of the available freshwater resources for other sectors like agriculture and industries. This has led to geopolitical disputes between SSA countries; a typical example of this is the current political dispute between Ethiopia and Egypt over the Nile river (73,74); Egypt relies on the Nile for irrigation, while Ethiopia which has the fountainhead of the Nile wants to generate electricity from the Nile to meet its growing energy demand. However, the application of IoT will mitigate such disputes because desired agricultural production can be attained with minimal dependence on natural resources.

On the agricultural productivity front, the application of IoT has the potential to increase food production significantly and bring about improvement in SSA's performance in livestock food supply and crop production. Such improvement will reduce the prevalence of malnutrition and other Sustainable Development Goal parameters, and break the low productivity levels which trap SSA farmers in poverty. An increase in productivity as a result of the application of IoT will also make it possible for SSA farmers to feed the rapidly expanding urban populations and at the same time generate exports capable of meeting demands in the global markets; this will be a strong impetus in the reduction of poverty, enhancement of food and nutrition security, and support for a more inclusive pattern of economic development. Another desirable application of IoT in agriculture in SSA is that farmers' productivity will become less vulnerable to the effects of climate change because the technology will ensure that all environmental parameters necessary for high productivity are closely monitored and maintained as much as possible with minimal impact on the environment.

IoT is a technology that is predicted to play a central role in realizing the worth of the agriculture value chain shown in Fig. 11. This is because each of the branches of the agriculture value chain on a global scale is estimated to be worth billions of dollars (75). The application of IoT in these branches will make it possible for SSA countries to generate and share data on their performance in the agriculture value chain; this will enable joint planning and resource development between SSA nations which in turn will enable SSA to shift focus from a trade-only region to an industrialized region capable of producing and processing its agricultural output. Such an achievement will further galvanize African regional integration, which is one of the objectives of the African Union (AU).

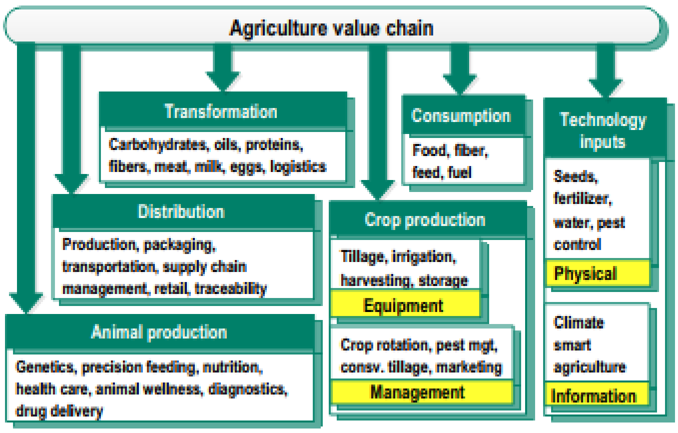

Figure 11. Agriculture value chain

As an example, consider the application of IoT in the crop production value chain and livestock value chain as depicted conceptually in Fig. 12. Information from the crops and livestock arrives at the data center via cell towers and satellites; they are then processed using artificial intelligence (AI) techniques to predict the best approach to use to get the best out of irrigation, harvesting, and also achieve precision feeding and wellness of livestock. Such an approach guarantees a significant increase in crop production and livestock production, thereby increasing the worth of the associated agriculture value chains.

A potential game-changer in SSA's quest to achieve self-sufficiency in food production is irrigation farming, and the deployment of IoT in irrigation will yield the desired level of productivity. The next section will look at irrigation in SSA and how IoT can be applied to it.

4.1. Irrigation and IoT Technology

According to (76), irrigation is one of the most effective ways of increasing national food supplies. This is because irrigation guarantees that all-year-round farming can be performed, which leads to all-year-round productivity and supply of food to meet the growing demand for essential foods and nutrition. Such all-year-round activity reduces the risk of drought and encourages crop diversification hence enhancing the income of rural farmers (77). SSA with the highest prevalence of food insecurity as shown in Fig. 2 and a high poverty rate stands to benefit most from irrigation if it is to meet its projected increase in demand for food and poverty reduction. However, to derive the maximum benefits from irrigation, SSA must practice what is known as "enhanced irrigation" which is a point of convergence between technology and irrigation practices.

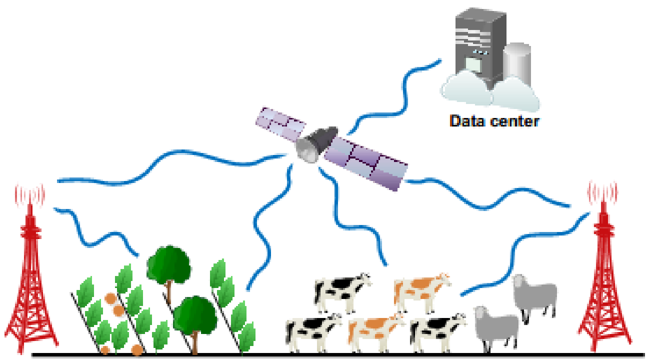

Figure 12. Application of IoT in crop production and livestock value chains

Enhanced irrigation involves the use of IoT in the effective management of natural resources associated with irrigation. This is very important because the water footprint associated with irrigation of crops, watering of livestock, and aquaculture accounts for 70 percent of total global water withdrawals (76). Enhanced irrigation is one sure way to reduce this footprint. While most global regions have shifted from traditional irrigation to enhanced irrigation using IoT, SSA is yet to make that shift as shown in Fig. 13(77), where the total land area in SSA equipped for irrigation is negligible in comparison to other global regions.

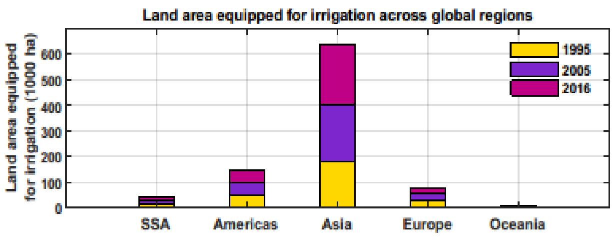

Figure 13. Total land area equipped for irrigation across global regions 1995 – 2016

4.2. Example of Application of IoT Technology in Irrigation

The role IoT solutions are envisaged to play in irrigation in combination with cloud computing systems includes optimal management of fresh water and other resources in real-time which will reduce the impact of irrigation on the environment. An example of such a solution is the IoT Cloud-Based Smart Irrigation System (IoT-CBSIS) which the authors developed to assist local farmers to attain optimal management of natural resources in our local environment. Fig. 14 shows the general concept of an automated smart irrigation system while Fig. 15 depicts the actualization of the concept. The system uses IoT devices to collect data from the connected irrigation farm and transmits the same through the gateway to the cloud. These data are analyzed via set algorithms, and output is used to control inputs in the farm. Users can view and manage their farms remotely.

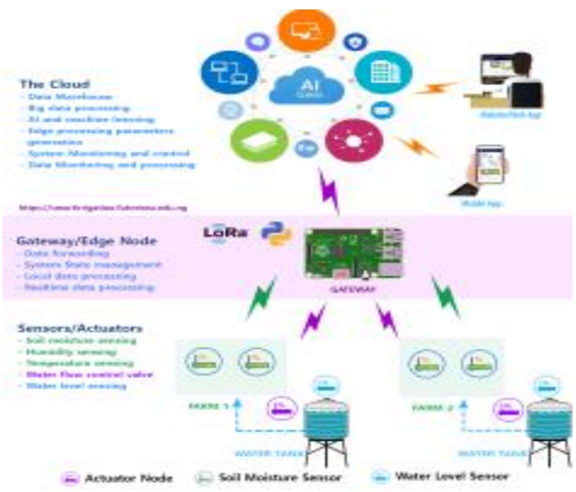

Figure 14. Automated smart irrigation conceptual diagram

In comparison to traditional irrigation, enhanced irrigation using IoT has numerous benefits as shown in Table 3. Despite its few disadvantages, the benefits of enhanced irrigation far outweigh that of traditional irrigation.

It should be noted that to maximally derive the benefits of enhanced irrigation through the application of IoT, a lot of data must be collected and analyzed frequently to ensure optimum decisions about the actions and control of IoT devices at all times. To achieve this feat, big agro-data collection, analytics, and prediction are involved in the acquisition and processing of data. The following subsections discuss these techniques in IoT agriculture.

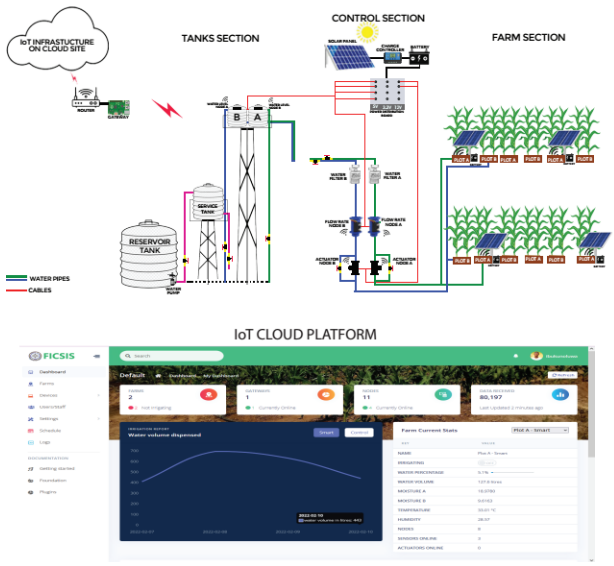

Figure 15. Developed IoT solution for optimal irrigation

Table 3. Comparison between traditional irrigation and enhanced irrigation in terms of advantages and disadvantages

Traditional Irrigation		Enhanced Irrigation	
Advantages	Disadvantages	Advantages	Disadvantages
It is cheap	Susceptible to the effects of climate change	Guarantees high productivity	It is expensive to start
Requires a few inputs	Leads to water scarcity	Has minimal impact on environmental resources	Requires a lot of input to integrate the system
Maintenance is not frequent	Remote monitoring is not possible, and it is also labor-intensive	Very resilient against the effects of climate change	Requires routine maintenance
		It is predictable	
		Remote monitoring is possible, and it also conserves water.	

4.3. Big Agro-Data Collection, Analytics, and Statistical Operations

4.3.1 Big Agro-Data Collection

Big agro-data collection can be defined as the collection of a large volume of data associated with agriculture which is wide in variety and at a high rate such that the creation and capture of such data are beyond the ability of relational databases to process and manage them without huge latency. Big agro-data is a special type of Big data whose primary source is derived from agricultural activities. Big data is broadly classified as structured or unstructured. Structured Big data which is often numeric is composed of information pre-processed by organizations, while unstructured Big data, which is not pre-processed is mainly obtained from social media sources and natural phenomena (78,79). As such, Big agro-data is unstructured Big data.

4.3.2 Big Agro-Data Analytics

One of the most important features of Big agro-data is that it contains a variety of unseen information, and the collection of such data provides critical insights into patterns and behaviors capable of enhancing irrigation if properly understood and harnessed. Table 2 shows the sources of a variety of information in Big agro-data. The analysis of the Big agro-data through the extraction of valuable patterns and hidden useful information is how such an unseen variety of information and phenomenon are usually discovered; as a result of this, Big agro-data analytics is one of the most important operations performed in data-intensive-driven agriculture. The extraction process begins with a preprocessing step which removes redundancy in data thereby increasing the quality of data. To be able to perform Big agro-data analytics, the architecture of the Big data must be supported by the infrastructure of the organization using such. To this end, organizations are constantly deploying open-source Big data tools to perform Big data analytics (79,80).

A leading open-source tool for Big data analytics is Hadoop which is a software framework written in Java and can operate on a chunk of a given data set. A desirable feature of Hadoop in Big data analytics is its ability to process a large set of data spread across clusters of computers (80). This is ideal for CSA because it is powered by IoT and cloud computing whose data sources originate from different geographical locations operating with different servers. A well-known Hadoop architecture is a V1.x architecture as shown in Fig. 16; it consists of two parts: the Hadoop Distributed File System (HDFS) which has a storage part and a data processing part, and the management (MapReduce) part (79).

Two processes make up the master node in Fig. 16 i.e. the job tracker and the name node. The job tracker is responsible for managing a given set of tasks, while the name node is responsible for the storage of the tasks. In the slave node, the task trackers are responsible for receiving tasks from the job tracker and processing them while the data nodes perform a similar task to that of the name node. The MapReduce layer is the data processing engine and it is also used for the management of cluster resources, while the HDFS layer is primarily responsible for handling the file-system component in the Hadoop ecosystem (79). Using this architecture, Hadoop can perform complex data analytics and statistical operations on Big data especially Big agro-data from which predictions can be made. These statistical operations include data mining, predictive analytics, machine learning, and deep learning.

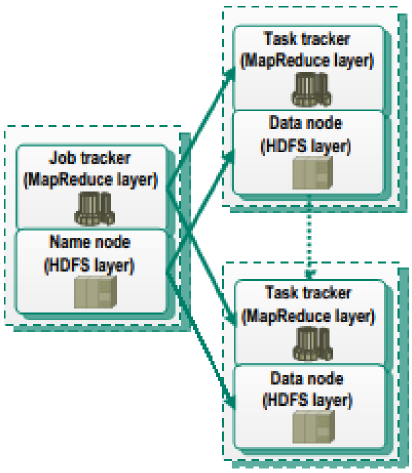

Figure 16. Hadoop V1.x architecture

4.3.3 Big Agro-Data Statistical Operations

Big agro-data statistical operations involve the use of artificial intelligence techniques on Big agro-data to predict environmental parameters which have a direct effect on the well-being of crops and livestock. Data mining, predictive analytics, machine learning, and deep learning are typical operations performed in statistical operations.

Data mining is the process of sieving through Big data to establish the existence of certain patterns and relationships. Data mining enables classification and clustering in Big data, and it also enables the development of association rules for members of Big data. In critical fields like agriculture with Big agro-data, data mining is extensively used for anomaly detection to forecast the occurrence of undesirable events and make proper planning for mitigating measures. There are three steps involved in data mining and they include exploration – this is the process of cleaning the data by removing redundancies and transforming it into a suitable form to extract important variables concerning the problem being solved. The second step is pattern identification – this is the process of selecting a pattern that makes the best-fit prediction of the data. The last step is deployment - this is the process of utilizing the data in an algorithm to obtain the desired outcome (81–85). To perform data mining, algorithms play a critical role. These algorithms are developed using different methods which include clustering, regression, artificial intelligence, neural networks, decision trees, genetic algorithm, and the nearest neighbor method (84,85).

Predictive analytics is a data mining technique that uses current data and historic data to make predictions about the likelihood of the occurrence of a future event. Large amounts of data with different variables as in the case of Big data are analyzed during predictive analytics, and the most common approach used includes: genetic algorithms, hypothesis testing, text mining, decision analytics, regression modeling, market basket analysis, and decision trees, and clustering. At the core of predictive analytics is a predictive variable that represents an entity whose future behavior can be predicted. When a combination of multiple predictors occurs, then a predictor model is said to be in existence that forecasts future probabilities within an acceptable level of error tolerance (86–91).

Machine learning is a field in computer science a technique in which existing data are used to predict or respond to future data by deriving a model from the data. Machine learning makes it possible to solve problems for which analytic models are difficult to develop. Fig. 17a depicts how a model is derived during a machine learning process, while Fig. 17b shows how the derived model is applied to field data.

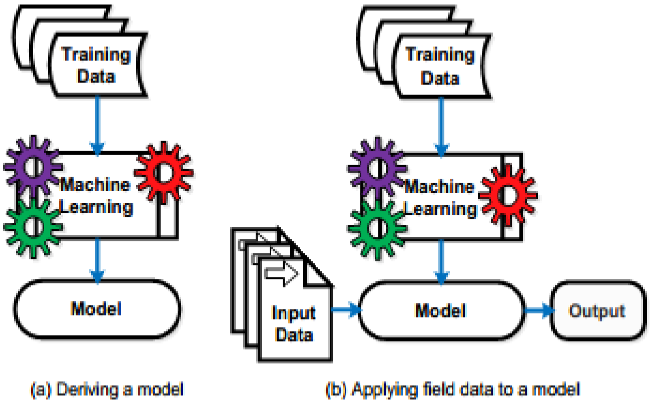

Figure 17. Machine learning processes

Broadly speaking, there are three types of well-established algorithms in machine learning enumerated below (92–94); these algorithms have their variants and hybrid.

- Unsupervised learning – this is when machine learning occurs by discovery and adaptation based on the observed pattern of input. The learning process occurs using clusters of data that have relationships between their members.
- Supervised learning – this is when machine learning occurs through the comparison of the computed output to the expected output. The error obtained from this comparison is adjusted using optimization techniques so that the computed output will be close as possible to the expected output.
- Reinforcement learning – this is learning based on long-term rewards. A reward is given when a correct output occurs and a penalty occurs when the output is wrong. This type of learning differs from (i) and (ii) in the sense that sub-optimal actions are not corrected, and a correct pair of input/output are never presented (92).

It should be noted that in machine learning, the consistency of the model irrespective of the training data relies heavily on the process called generalization.

Deep learning is a special group of machine learning algorithms and techniques which exploit a large number of possible layers in a non-linear information processing procedure for the sole purposes of pattern analysis and classification, supervised feature extraction, and unsupervised feature extraction. Deep learning distinguishes itself from other machine learning techniques in the sense that it does not require domain expertise in the design of feature extractors; it can in its activities as a feature extractor by automatically transforming low-level features into higher-level features by identifying very small and “irrelevant” variations in a Big data. This makes deep learning far more accurate than other machine language techniques. At the heart of deep learning is the technique called representation learning, and it is a process of autonomous feature selection through the multi-layered representation of input data (95–99).

At the heart of deep learning is a special class of neural networks called deep neural networks, and they are defined as neural networks that have two or more hidden layers. The deep neural network is equivalent to a model in machine learning, and it is usually derived from a set of learning rules. Fig. 18 illustrates this concept, where it can also be seen how field data is applied in deep learning.

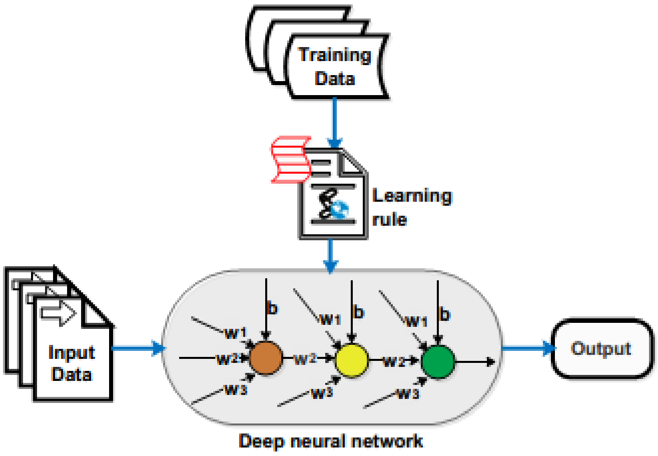

Figure 18. Deep learning process

Multivariate adaptive regression splines are a data-driven modeling technique that is based on a multivariate nonparametric regression approach and it does not take into account the functional relationship between the input and output data. Through a divide-and-conquer approach, training data sets are broken into separate piecewise linear segments called splines with differing slopes. Knots are used in delimiting the segments by marking sub-divisions between any adjacent data regions in such a way that it is possible to obtain piecewise curves called basis functions (BFs) (100–103). Mathematically, MARS can be expressed as (102):

$$y = C_0 + \sum_{i=1}^{N} C_i \prod_{j=1}^{k_j} b_{ji}\left(x_{\vartheta(j,i)}\right) \quad (1)$$

where y is the output variable, C_0 is a constant, C_i is the vector of coefficients associated with basis functions which are not constant, $b_{ji}\left(x_{\vartheta(j,i)}\right)$ is the basis function with truncated power and having $\vartheta(j,i)$ as the index of the independent variable used in the i^{th} term of the j^{th} product, and k_j is a parameter that limits the interaction order.

For any spline b_{ji}, it can be defined as (100–103):

$$\begin{aligned} b_{ji}(x) &= \left|x - t_{ji}\right|_{+}^{q} = \begin{cases} \left(x - t_{ji}\right)^q & if \quad x < t_{ji} \\ 0 & if \quad x \geq t \end{cases} \\ b_{ji+1}(x) &= \left|t_{ji} - x\right|_{+}^{q} = \begin{cases} \left(t_{ji} - x\right)^q & if \quad x < t_{ji} \\ 0 & if \quad x \geq t \end{cases} \end{aligned} \quad (2)$$

where t_{ji} is the knot of the spline, $q(q > 0)$ represents the spline power and the degree of smoothness of the resultant function approximation. The determination of the basis function to be included in the model is done by generalized cross-validation (GCV) which is the mean of the squared residual error divided by a penalty whose complexity depends on the model and is mathematically expressed as (102):

$$GCV = \frac{1}{N}\sum_{i=1}^{N}\left[y_i - f(x_i)\right]^2 \Big/ \left[1 - \frac{M + d \times (M-1)/2}{N}\right]^2 \quad (3)$$

where M is the number of bases functions, d is the penalty for each basis function in the sub-model, N is the number of data sets, and $f(x_i)$ the predicted values by MARS.

Sections 5.0, 5.2.1, 5.2.2, and 5.2.3 all point to the enormous benefits that can be derived from the application of IoT and cloud computing in agriculture which will ultimately lead to CSA and quite several researches have been made in this direction as discussed in section 5.3. However, the application of such technologies in SSA comes with certain challenges as will be shown in section 5; nevertheless, such challenges are surmountable.

4.3.4 Review of Current and On-going Research in the Application of Cloud Computing, IoT, and Big Data Analytics in CSA

IoT has been successfully applied in the smart monitoring of agricultural land which has resulted in the efficient maintenance of critical parameters like temperature level, water level, and humidity level (104). To perform smart monitoring, three important sensors were deployed: temperature sensor, water flow sensor, and soil moisture. Data obtained from these sensors were centrally controlled by a PIC microcontroller which was programmed to activate and deactivate subsystems necessary for the maintenance of the parameters being monitored.

In (104), the authors fully automated a farm with an array of sensors and actuators all connected to an Arduino microcontroller. In their arrangement, temperature and humidity information was collected by the sensors and sent to a web server which then compared the information with the forecasted rainfall for the region. Depending on the outcome of the comparison, a report is sent to the user on whether or not to activate the irrigation system on the farm. Optimum water utilization was achieved by the automated farm.

A technique called FarmBeat was proposed in (105) to boost agricultural productivity by reducing losses and increasing yields. It is an end-to-end IoT platform for agriculture that makes it possible to perform seamless data collection from cameras, drones, and sensors. FarmBeat is a robust design that has been shown to support agricultural activity for almost six months in the presence of power and internet outages. Connectivity on the farm was achieved by utilizing unlicensed TV white spaces for the establishment of a high bandwidth link from the farmer's home internet connection to an IoT base station located on the farm. From this connection, the IoT was able to push data to the cloud which was accessible to farmers at remote locations from the farm.

Using Fipy board, Pysense board, Pycom expansion board, and Raspberry Pi, the authors in (106) created an IoT system that consisted of two nodes i.e. node 1 and node 2, and a gateway which was all formed using Pysense, Fipy, external LoRa antenna, and a Raspberry Pi 3 application processor. Node 1 was used in communicating temperature and humidity data, while node 2 was used in communicating barometric and ambient light data. Using MQTT protocol, a server that acted as a cloud received information from nodes 1 and 2 for processing and storage. A farmer with either direct or remote access to the server could obtain critical information about the environmental condition to make data-driven decisions that will impact positively on productivity.

AGRIoT was proposed in (107); the system had three units which include a fertilizer sanction unit based on soil nitrogen, potassium, and phosphorus values, an estimation unit for water cropping, and an irrigation scheduling unit. For any crop type selected, AGRIoT used an evapotranspiration algorithm to determine the desired water level for the crop.

IoT and machine learning were combined by (108) to achieve automation in agriculture. Their technique automated the monitoring of soil conditions by monitoring parameters like temperature and humidity, water level, and moisture content. To perform this automation, Arduino UNO was used for the collection of sensor values and then transmitted to a Raspberry Pi in which an Apache Web server was set up. The Raspberry Pi also had an SQL database of data storage. Communication between the sensors and the server was established using the Zigbee module; this enabled the transmission of data in real-time to the server which a farmer can access anytime thereby reducing the required amount of man-hour needed for farm monitoring.

Smart irrigation and agriculture-based monitoring were performed (109) using Raspberry Pi which was used to control an array of monitoring sensors. The sensors monitored important parameters like soil moisture, humidity, and temperature. An irrigation system was triggered when the soil moisture level goes low. Data from the sensors and processes by Raspberry Pi was retrieved by ThingSpeak which is an open-source cloud platform. The application of IoT and related digital solutions is still in its infancy. Therefore, there are attendant challenges that indigenous research and policies are yet to solve in this area, especially as it concerns sub-Saharan Africa.

5. Challenges, Solutions, and Open Issues in Application of IoT in Agriculture in SSA

In the application of IoT in agriculture in SSA, several challenges must be overcome if IoT is to become ubiquitous with universal penetration across the continent. These challenges include finance, illiteracy, technical skills, and local content.

Finance is a major determinant in the success of the application of IoT in agriculture because the cost of commercial IoT devices is on the high side for most low-income countries, especially in SSA (110). As a result of this, any attempt by SSA countries to deploy IoT in agricultural programs may be impeded by finance.

Illiteracy is another challenge that undermines the successful implementation of IoT in agriculture in SSA in the sense that about 37% of the adult population in SSA still lacks basic literacy skills which translates to 170 million people (111),(112). By implication, this staggering figure imperils the digital literacy level in SSA; hence the ability to effectively analyze and create digital content among SSA farmers is lacking in most cases. As a result of this, maximum benefits and ease of information access through IoT deployment are yet to be achieved in SSA.

Technical skills are tangential to the success and widespread acceptability of IoT in agriculture in SSA because they keep IoT in a functional state in which the IoT can meet the wide spectrum of demands in agriculture in SSA. Sadly, in most SSA countries, the requisite technical skills to ensure the availability of IoT as a technology is lacking (112); the implication is that frequent down-time is experienced in the most application of IoT in agriculture, and this has dampened the enthusiasm of SSA farmers to fully embrace IoT.

Local content is a challenge in the application of IoT in SSA because the development of mobile applications and digital content in almost all cases does not take into account the contemporary reality of the African end-user (110–112). These applications and digital content which are mostly developed in advanced countries do not make provision for customizations of content that suit SSA's peculiar needs and languages. As a result of this, most SSA farmers view IoT technology from an unfriendly perspective.

5.1 Proposed Solutions to the Challenges in the Applications of IoT in Agriculture in SSA

The challenges highlighted in section 5.0 are not insurmountable as long as the right steps in the right direction are taken. In this section, we propose a three-prong approach as depicted in Fig. 19 which can effectively mitigate the challenges associated with the application of IoT in agriculture in SSA.

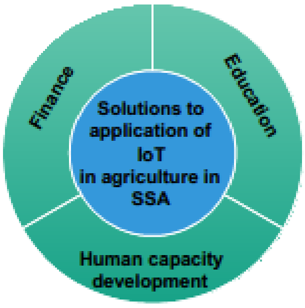

Figure 19. Solutions to the challenges in IoT application in agriculture in SSA

Finance as a solution to the challenge in IoT application in agriculture in SSA deals with making commercial IoT devices affordable through subsidies and single-digit loans from financial institutions. This will encourage SSA farmers to become more active players in the application of IoT in agriculture. The subsidy is envisaged to come from SSA governments through ministries and departments of agricultural development while single-digit loans are envisaged to come from specialized financial institutions like agricultural development banks. Also, international aid should not come in terms of food aid to SSA but in terms of financial and advisory aid to enable SSA to produce their food and become self-sufficient in food.

Education addresses the problem of illiteracy by making sure the adult population has access to basic education. This will, in turn, have a positive impact on digital literacy especially among SSA farmers; accessing and analyzing digital content will thus become easier and hence deriving maximum benefits from the application of IoT amongst SSA farmers will be achieved.

Human capacity development addresses the problem of technical skills and local content development in the sense that specialized and targeted training can be made which addresses specific manpower gaps in the maintenance of IoT systems. This will go a long way in ensuring that IoT systems can be adequately maintained within the local environment. On the local content front, human capacity development will enable the training of local digital content developers who will develop digital contents and solutions which are native to the challenges faced by SSA farmers. These contents can even be developed in local languages that are mostly understood by the end-users.

5.2 Open Issues in the Application of IoT in Agriculture in SSA

Despite all the identified challenges and associated solutions to the application of IoT in SSA, there are still several open issues and areas which need to be addressed if SSA is to make the necessary quantum leap in food security. A well-known open issue is research and development (R&D) in agriculture (113). SSA needs to make concerted efforts in research and funding research in agriculture if SSA is to address its peculiar environmental challenges using IoT as it affects agriculture. Fig. 20(113) shows that in comparison to other global regions, SSA public spending on agriculture and funding of research in agriculture is abysmal. This situation needs to be reversed by deliberate government policies and interventions.

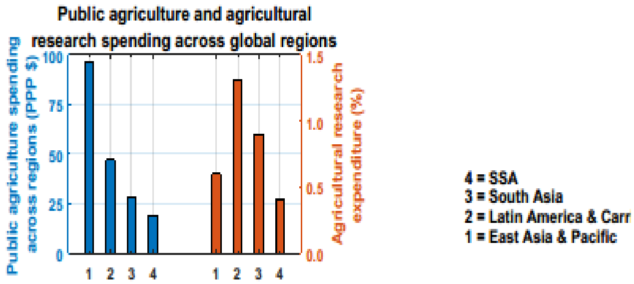

Figure 20. Public agriculture-related expenditures across developing regions

Conclusion

The quest to achieve global food security is no doubt a long and odious task, but it is also achievable. This can be done if vulnerable regions of the world are carried along and encouraged to also achieve self-sufficiency in all developmental indices. SSA is one particular region that falls into this category. Despite having the largest arable land in the world, SSA's performance in its attempt to achieve food security has at best been abysmal and unacceptable. In this paper, an overview of the problem of food insecurity in SSA was presented by first appraising the current status of SSA's food insecurity and the aggravating factors. The paper also examined how trade and post-harvest activities have affected SSA's ability to achieve food sufficiency. Considering the impact of prevailing climate change on food security, the idea of climate smart agriculture (CSA) was discussed alongside its associated technologies like IoT, cloud computing, and data analytics, and how they can be harnessed to increase agricultural productivity across SSA with minimal impact on the environment. Finally, the paper looked at the challenges associated with the implementation of IoT in SSA and the associated solutions that can be proffered to mitigate such challenges.

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Conflict of Interest
The authors do hereby declare that there was no conflict of interest in the course of this study

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