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PRECISION AGRICULTURE IN NIGERIA: THE IMPACT OF AI ON FARMING PRACTICES AND SUSTAINABILITY

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Abstract

Nigeria, a prominent global producer of diverse crops, confronts persistent challenges in meeting domestic agricultural demands, despite government and development partner interventions. This paper delves into the utilization of Artificial Intelligence (AI) in agriculture as a potential solution to enhance food production, addressing the escalating predicaments faced by the agricultural sector in Nigeria. The agricultural landscape of Nigeria encompasses essential crops such as cocoa, palm oil, rice, cassava, maize, guinea corn, yam, beans, and millets, complemented by a substantial livestock population consisting of goats, sheep, cattle, and poultry. However, these endeavors are beleaguered by multifaceted challenges including disease outbreaks, pest infestations, water scarcity, inadequate drainage systems, labor scarcity, and a technology divide between farmers and innovation. Contributing to this landscape are hindrances like limited financial access, climate change ramifications, land degradation, and fragmented market accessibility. Additionally, Nigeria's projected population surge to exceed 400 million by 2050 underscores the pressing need for substantial food production enhancement.

Historically, attempts at augmenting food production have centered on expanding cultivated lands and intensifying fertilizer and irrigation use, alongside reducing pre-harvest, harvest, processing, and distribution losses. However, this trajectory poses threats such as soil depletion, water scarcity, deforestation, and elevated greenhouse gas emissions. To counterbalance these adverse effects, the incorporation of AI-driven precision farming emerges as a transformative solution. The convergence of AI technologies with agricultural practices offers innovative avenues for improving productivity, resource utilization, and sustainability. This paper examines the diverse applications of AI

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in agriculture and investigates the manifold opportunities and challenges inherent in their implementation within Nigeria's agricultural context. By leveraging AI-powered solutions for crop monitoring, disease prediction, precision irrigation, and supply chain optimization, Nigerian agriculture can evolve into a dynamic, technologically-driven sector capable of meeting the demands of a burgeoning population and addressing pressing environmental concerns.

1. INTRODUCTION

Nigeria is a leading producer of many crops such as cocoa, palm oil, rice and cassava, maize, guinea corn, yam, beans, and millets (Onwualu, 2012). Livestock mostly reared by farm families in Nigeria are the small ruminants like goats (76 million), sheep (43.4million), and cattle (18.4 million). In addition, poultry population stands at 180 million poultry (FAO, 2018). However, domestic demands generally outstrip production, despite several interventions by the government and development partners to improve production. The agriculture sector faces numerous challenges including disease and pest infestation, insufficient available water, inadequate drainage, declining labour availability and knowledge gap between farmers and technology, leading to low output. As enumerated by Njoku (2000) and Ugwukah (2020), other challenges are low technology, high production cost and poor distribution of inputs, limited financing, climate change and land degradation, high post-harvest losses and poor access to markets.

The population of the country was predicted to exceed 400 million people by year 2050 (World Bank, 2022). To avert a looming food crisis, a significant improvement must be made to food production. Efforts, before now, have been concentrated on increasing the amount of agricultural land put under cultivation and the increased use of fertilizers and irrigation. Also, attempts have been made at significantly reducing food loss (at pre-harvest, harvest, processing and distribution stages in the food supply chain). However, cultivation of more lands is poised to leads to depletion of soils, water scarcity, widespread deforestation and high levels of greenhouse gas emissions (Koneswaran and Nierenberg, 2008; Oertel et al., 2016; Rojas-Downing et al., 2017). Adopting new methods like precision farming, with the application of AI to agriculture holds great promise. This paper reviews the applications of AI to agriculture and considers the opportunities and challenges it holds for Nigeria.

2. THE CONCEPT OF AI

AI, also called machine Intelligence, is intelligence demonstrated by machines in contrast to natural intelligence displayed by humans and other animals (McCorduck, 2004). John McCarthy, who is popularly known as the ‘Father of AI’ (Anderson, 2002 and Rajaraman, 2014), described AI as the science and engineering of making intelligent machines, especially intelligent computer programs (McCarthy, 2007). Intelligence itself has been defined as that quality that enables an entity to function appropriately and with foresight in its environment (Nilsson, 2010). It has also been described as a general mental ability for reasoning, problem solving, and learning. Because of its general nature, intelligence integrates cognitive functions such as perception, attention, memory, language, or planning.

According to Abonamah et al., 2021, there are three types of AI: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI) and Artificial Super Intelligence (ASI). The first type, which is ANI, also known as ‘weak’ AI, has narrow range of abilities. ANI can usually perform a single task—whether it is driving a car, playing chess, or recognizing spoken or written words. Although ANI systems are designed to focus on their tasks in real-time, with continuous learning from their environments, they are able to build knowledge over time and become experts in performing their assigned tasks (Beaulac and Larribe, 2017). Thus, ANI is the most common and coherent kind of AI to be utilized by most people.

AGI is the hypothetical ability of an intelligent agent to understand or learn any intellectual task that a human being can perform (Colom et al., 2010). This involves the ability to achieve a variety of goals, and carry out a variety of tasks, in a variety of different contexts and environments. A generally intelligent system should be able to handle problems and situations quite different from those anticipated by its creators (Goertzel, 2014). There are yet no existing intelligent agents that possess the AGI properties, and progress in that direction had been slow (McCarthy, 2007). We still look forward to the day when a computer or a system is better than a human being – wiser, more creative, and more socially adept.

ASI is a hypothetical ability of an intelligent agent to possess intelligence substantially exceeding that of the brightest and most gifted human minds. Currently, it is not technologically possible to produce machines that possess super intelligence properties. The computer is becoming an intelligent machine and there are indications that its level of intelligence may eventually surpass that of its human creator. If such a scenario comes true, then AI will transit in rapid succession to what is now commonly referred to as AGI, and then exponentially to ASI (Jens, 2015). Already, there are lots of worries about the social and ethical consequences of this development (Gill, 2016)

Generally, AI techniques simulate human intelligence (Ayed and Hanana, 2021) and rely heavily on machine learning (ML) for most applications. ML uses statistical and mathematical methods to learn from datasets and to make data-driven predictions or decisions. The ML approach is classified into three major tasks: supervised, unsupervised, and reinforcement learning (Alloghani et al., 2020; Sharma et al., 2020). In supervised learning, the aim is to map the input variables to the preferred output variable. In supervised learning, the ML algorithm is given a training dataset, usually between 75 and 80% of the total data set, to work with (Longstaff et al., 2010; Bohani et al., 2021). This training dataset serves to give the algorithm a basic idea of the problem, solution, and data points to be dealt with. The algorithm then finds relationships between the parameters given, essentially establishing a cause and effect relationship between the variables in the dataset. At the end of the training, the algorithm has an idea of how the data works and the relationship between the input and the output. Unsupervised machine learning holds the advantage of being able to work with unlabelled data, allowing much larger datasets to be worked on by the program. Relationships between data points are perceived by the algorithm in an abstract manner, with no input required from human beings (Karamzadeh and Moharrami, 2015; Sarker 2022).

Reinforcement learning directly takes inspiration from how human beings learn from data in their day to day lives (Shteingart and Loewenstein, 2014; Dayan and Balleine 2002; Najar and Chetouani, 2021). It features an algorithm that improves upon itself and learns from new situations using a trial-and-error method. Favourable outputs are encouraged or 'reinforced', and nonfavourable outputs are discouraged or 'punished'. Based on the psychological concept of conditioning, reinforcement learning works by putting the algorithm in a work environment with an interpreter and a reward system (Wu et al., 2018). The output result is given to the interpreter in every iteration of the algorithm, which decides whether the outcome is favourable or not. In typical reinforcement learning use-cases, such as finding the shortest route between two points on a map, the solution is not an absolute value. Instead, it takes on a score of effectiveness, expressed in a percentage value. The higher this percentage value, the more reward is given to the algorithm. Thus, the program is trained to give the best possible solution for the best possible reward. (Judah et al., 2014; Cederborg et al., 2015; Najar and Chetouani, 2021).

3. APPLICATIONS OF AI IN AGRICULTURE

According to the Food and Agriculture Organizations of the United Nations (FAO 2019), by 2050 global food production should increase by 70% to feed 9.6 billion people worldwide. Unless some drastic measures are taken, there may be disasters of food shortages (Nelson, 2010). For most of the 20th century, many key factors influenced the increases witnessed in food production: mechanization leading to cultivation of more lands, improved genetics and increased use of inputs. Notably, much of the land not yet in use today suffers from constraints (chemical, physical, endemic diseases, lack of infrastructure, etc.) that cannot easily be overcome or that it is not economically viable to do so (FAO, 2009). Providing effective solutions to these old and new challenges require new insights. AI techniques when applied to agricultural processes tend to increase productivity and efficiency. AI-powered solutions will not only enable farmers to do more with less, it will also improve quality and ensure faster go-to-market for crops. Major applications areas are now briefly considered:

i. Farm monitoring.

The success of the farm enterprise is completely based on the end yield and the market rate. Crop yield depends on timely monitoring and scientific prescription of appropriate remedies (Jha et al., 2019; Dharani et al., 2021). During the production season, it is sometimes necessary to obtain visual indications of crop growth along with the geographic locations of those areas. AI and Internet of things (IoT) based monitoring systems give a precise extraction and analysis of data. The effect of physical conditions like humidity, temperature, soil temperature and moisture and light intensity on the plant growth, is monitored using IoT based monitoring system. (Leon et al., 2003; Alreshidi, 2019; Singh et al., 2020). AI furnishes a precise way to monitor the crop and to predict the yield in an automatic way.

Robots, enabled by AI, have been employed to monitor respiration, photosynthetic activity, yield and other biological factors (Wang et al., 2012, Hamner et al., 2012). They have also been employed in pollution monitoring: measuring carbon dioxide and nitrous oxide emissions so that farmers can reduce their environmental footprint.

ii. Plant's disease and insect detection.

Plant diseases and insect pests contribute to production loss, which can be tackled with continuous monitoring. Manual plant disease monitoring is both laborious and error-prone. Early detection of plant diseases using computer vision and AI can help to reduce the adverse effects of diseases and also overcome the shortcomings of continuous human monitoring (Abu-Naser, 2010; Chowdhury et al., 2021; Suhag et al., 2021). Plant Disease detection systems use various sensors to collect the plant-related data in form of images at different time intervals (Martinelli, et al., 2015; Win, 2018; Selvari et al., 2019; Hong et al., 2020; Suhag et al., 2021; Liu and Wang 2021; Chen et al., 2021; Li et al., 2022).

iii. Intelligent farm chemicals application.

Most conventional sprayers apply agrochemicals uniformly, despite the fact that distribution of weeds and pests is typically random or patchy, resulting in wastage of valuable compounds, increased costs, crop damage risk, pest resistance to chemicals, environmental pollution and contamination of products (Chen and Li, 2019; Idoje et al., 2021; Mohamed et al., 2021; Javaid et al.,2022). Smart sprayers utilizing machine vision and artificial intelligence to distinguish target pests or weeds from non-target objects (e.g. vegetable crops) and precisely spray on the desired target/location are of great importance. Detection of unwanted pests on crops, or weed detection, is implemented with frame-capturing drone (Partel et al., 2020, Partel et al., 2021; Hafeez et al., 2022) and deep learning methods.

Weeding is a very labour intensive and costly farm activity in Nigeria. Reducing the physical hardship, cost and time spent on such activities will increase the overall land yield, and losses due to failure of crops. There are robots that can autonomously navigate a farm and deliver targeted sprays of herbicides help eliminate weeds (Slaughter et al., 2008 and Shapiro et al., 2009). Some crop-dusting robots also apply other agrochemicals (Hair 2016).

iv. Weeding.

Weeds are unwanted plants that grow on farmlands and compete with crops for nutrients, space, and sunlight. If not removed, they obstruct crop growth, causing a reduction in crop yield and consequently, a reduction in profit for farmers (Marco et al., 2021). Efforts combining computer vision with traditional machine learning and deep learning are driving progress in weed detection and robotic approaches to mechanical weeding. Weed control robots are designed based on real-time image detection as the early identification and control of weeds is paramount. Development of a visual method of discriminating between crop seedlings and weeds is an important and necessary step towards the automation of non-chemical weed control systems in agriculture, and towards the reduction in chemical use through spot spraying (Aitkenhead et al., 2003; Partel et al., 2019; Andujar and Martinez-Guanter, 2022). Weeding robots are now becoming commercially available (Shiba and Miwa, 2022). These effectively save efforts while reducing environmental pollution caused by pesticide use (Mishra, 2021).

v. Aerial survey and imaging.

Drones, also called unmanned aerial vehicles (UAVs), are mostly associated with military, industry and other specialized operations, but with recent developments in area of sensors and Information Technology in last two decades, the scope of drones has also been widened to agriculture (Puri et al., 2017; Kim et al., 2019; Liu et al., 2021). Drone and global positioning systems (GPS) technology is giving agriculture a high-tech makeover. Drones have been useful in field, soil analysis and land management, planting, crop spraying / fertilizer application, farm monitoring / surveillance / health assessment, crop yield prediction etc. (Colomina and Molina, 2014; Veroustraete, 2015; Santangeli et al., 2020; Roslim et al., 2021; Jung et al., 2021; Alghamdi et al., 2021; El-Hoummaidi et al., 2021). In irrigation, drones have helped to identify which parts of a field are dry or need improvement (Talaviya et al., 2020).

vi. Produce grading and sorting.

Agricultural produce is graded based on their dimensions and other attributes. This grade is used to sort and assign them to different classes, and sometimes to different sales channels. More recently, as image processing algorithms emerged, visual inspection techniques provided a substitute to the human eye, enabling to detect many defects, which humans cannot detect when pace becomes faster (Mushiri et al., 2020; Thuyet et al., 2020; Menon et al., 2021). The new wave of intelligent algorithms for grading and sorting is much more powerful than traditional visual analysis algorithms: they have automatic learning capabilities, which ensure a detection performance far beyond the speed and accuracy of any trained operator. There are sorting and grading systems for eggs (Patel et al., 1998), tomatoes (Kaur et al., 2018), mangoes (Thinh et al., 2019, Thong et al., 2019) and garlics (Thuyet et al., 2020).

vii. Ploughing, Planting and other field operations.

GPS-enabled, tele-operated, and autonomous tractors and harvesters (De-An et al., 2011; Reid et al., 2016; Grose, 2022) have also hit the markets. Accurate steering through crop rows that avoids crop damage is one of the most important tasks for agricultural robots utilized in various field operations, such as monitoring, mechanical weeding, or spraying. In practice, varying soil conditions can result in off track navigation due to unknown traction coefficients so that it can cause crop damage (Kayacan et al., 2015). With advanced GPS, a tractor operator can tell which rows have been planted to avoid overlap, making sure every seed is in the right place, with the right depth, soil contact, and spacing that it needs to grow into a food-producing crop. GPSenabled self-driving tractors and self-propelled equipment confer an additional level of accuracy to the farming operation, and John Deere said it augments that GPS signal with a real-time kinematic (RTK) system that provides pass-to-pass accuracy of ±1 inch (Pele, 2021).

Intelligent robots that plant seeds possess automatic navigation in an agricultural area, and sowing seeds into the soil over a predefined map. With a robotic arm in the robot operating system, most setup have multiple sensors, to aid their work (Hassan et al., 2016). Additionally, some agricultural robots now have the ability to protect crops from harmful weeds that may be resistant to herbicide chemicals that are meant to eliminate them. To move plants around large greenhouses, including nursery automation, robots are also being used (Belforte et al., 2006). Robotic fruit and vegetable pickers (Bac et al., 2014) can work around the clock for faster harvesting. These robots are capable of harvesting crops at a much faster pace and higher volume than human workers.

viii. Automation of irrigation

The optimal use of water through irrigation has always been inextricably linked to the evolution of agriculture and successful farming. But efficiently managing natural water resources alongside a standard cost-benefit analysis for technology and infrastructure overheads is a delicate balancing act. With food demands only rising, water use is expected to increase an additional 15% to meet this demand (World Economic Forum, 2021). The importance of reducing water consumption is paramount, especially as agriculture is estimated to account for over 70% of global water use (Parris, 2011; Gruère, 2020). AI analysis of plant behaviour is a powerful tool that allows irrigation fine-tuning. Automatic plant irrigators are planted on the field through wireless technology for drip irrigation. Timely prediction of irrigation requirements and crop yields is necessary for farmer's welfare and satisfaction. The beforehand prediction significantly contributes to minimizing production cost and maximizing crop yields (Arvind et al., 2017; Jha et al., 2018; Sinwar et al., 2020; Chougule and Mashalkar, 2022). The precise prediction of crops' yields is also useful in planning various schemes, transport needs, buying mechanisms, storage infrastructure, and actual selling of crop by farmers to market (Vijayakumar and Balakrishnan, 2021).

ix. AI for Livestock, Fish and Poultry Farming

AI helps livestock farms accumulate and analyse data to accurately predict consumer behaviour, like buying patterns, leading trends, etc. With increased investments, farms will be enabled to automate processes, reduce major costs and improve the quality of livestock products like milk (Morrone et al., 2021).

There are now techniques for monitoring the health of farm animals with a high degree of accuracy using a camera and AI to achieve a "smart" cow-house or poultry house (Emanuelson,1988). Detailed observation by AI-powered image analysis has enabled early detection of injuries and illnesses that could impact the quantity and quality of milk production (Castro and New, 2016; Thilagu and Jayasudha, 2022). Facial recognition systems (Kumar and Singh 2018, Marsot et al., 2020), also monitor animals via cameras located, sometimes, on the roof of the barn. The data is then sent to a server on the farm. The main goals are to utilize the data to maximize production and limit stress levels on the animals. Tackling parasites, biosecurity, and diseases and advanced monitoring farm animals are now possible (Ernane and Costa, 2009; Phiri, 2018; Garcia et al., 2020,). Robots are also used for detection of oestrus (Saint-Dizier and Chastant-Maillard, 2012; Mottram, 2016), to deliver vaccines (Kumari and Dhawal, 2021) , detection of avian diseases or nutritional deficiencies in chicks (Sawabe,2006; Zhuang, 2018), detection of behavioural diseases like cannibalism (or aggressive pecking) (Mohanty et al., 2021; Mott, 2022).

For monitoring the animals on a farm and their health, internet of things (IoT) devices employing different types of sensors video/image processing and classification capabilities, along with vocalization (sound) based livestock analysis have been a subject of intense research (Chaudhry et al., 2020; Congdon et al., 2022; Michie et al., 2022; Wang et al., 2022). Availability of growingly inexpensive computational resources, IoT devices, and standard algorithms, has made a strong case to employ modern day technology to continuously monitor the large farms with millions of birds and improve the overall productivity (Saint-Dizzier and Chastant-Maillard, 2012; Shinde 2014; Singh et al., 2020; Neethirajan, 2020; Neethirajan and Kemp, 2021). IoT devices are used to monitor the locations of cows and eradicate cattle theft. They can detect the fertility and health of cows ranging from single cows to herds. An IoT device mounted on the neck of a cow tracks its activity throughout the day. The IoT device also sends information about health issues and eating behaviour to farmers (Unold et al., 2020, Chaudhry et al., 2020). The IoT devices are even used to milk cows (Righi et al., 2020, Akbar et al., 2020). They can also increase the production of milk by allowing cows to select when they would like to be milked.

Livestock herding on large ranches now engages robots. Examples include robotic feeding stations for livestock (Bergerman et al., 2016), robotic milking stations and dairies (Holloway et al., 2014; Schewe and Stuart 2015); slaughterhouses (Nielsen et al., 2014), meatpacking (Barbut, 2014). Remote inspection of agricultural infrastructure, especially fences and watering systems have also been reported (Puri et al., 2017).

x. Traceability and Supply Chain Management – Block chain technology

It is well known that consumers are increasingly becoming interested in where their food comes from and how it is produced. The adoption of AI in the food supply chains (FSC) can address unique challenges of food safety, quality and wastage by improving transparency and traceability

(Leung et al., 2021; Dora et al., 2022). There have been successful experiences regarding the integration of blockchain with AI techniques for product traceability improvement (Wamba and Queiroz, 2020). Blockchain can connect all aspects of the supply chain from producer to consumer and allow for food traceability and safety. From an agriculture and food perspective, offering this type of information to consumers will become a competitive advantage.

On a national scale, advanced logistics, transportation, storage, and processing are also crucial for making sure that food goes from where it grows in abundance to where it does not (Elferink, and Schierhorn, 2016). AI can significantly help trading companies to have a much greater impact on food security, because they source and distribute our staple foods and the ingredients (Allen, 1999). The strategic grain reserves agencies can leverage on data and AI to store periodically produced grains and oilseeds so that they can be consumed all year, and they process soft commodities so that they can be used further down the value chain.

xi. Farm management: optimisation of farming operations and decisions

Precision agriculture (PA) is seen today as a key technological solution enabling the more efficient use of agricultural resources (Nikki, 2015; Linaza et al., 2021). The goal is the increase of farmers' profits by improving harvest and/or quality yields, while reducing inputs, and the negative impact of farming on the environment, e.g., such that stems from the over-application of pesticides and fertilizers, and inefficient irrigation.

The emergence of new technological trends like AI enables farmers to take a data-driven approach to collect and analyse large amounts of data to gain knowledge about the real-time status of their fields to improve farm yield and mitigate risks from weeds, pests, and diseases. Based on multiple parameters like soil condition, weather forecast, type of seeds and infestation in a certain area and so on, cognitive solutions make recommendations to farmers on the best choice of crops and hybrid seeds (Sarangi et al., 2020). The recommendation can be further personalized based on the farm's requirement, local conditions and data about successful farming in the past.

External factors like marketplace trends, prices or consumer needs may also be factored into enable farmers take a well-informed decision.

AI can optimize and carry out particular activities such as planting and harvesting, increasing productivity, improving working conditions and using natural resources more efficiently. Digital technologies being used for precision farming gather data from farmers and public data sources evaluate by algorithms and provide the inputs to aid production and increase the farmer's return on investment. Thus, they provide insights on what to plant and the best time for farming to yield good proceeds. As the machine learning system gets more input on new data, and trains on them it becomes stronger and more effective, the system can identify abnormal crop conditions or farming situations before what the human eye can detect them. The intelligence generated by the system also make proactive and real-time decisions possible to prevent future issues (Evans et al., 2017).

4. AI IN NIGERIA'S AGRICULTURE: THE POTENTIALS

Currently, the yield gap—the difference between a crop's potential yield and actual yield— exceeds 76 percent for many crops in Nigeria (Babatunde et al., 2017; Rong et al., 2021). There are therefore enormous potentials for improvement in farm productivity in the country. AI can help meet rising demand for food and support a more inclusive and sustainable food system by enhancing the resilience of farming methods; reducing the cost of inputs and services to underserved farmers; and improving market access to facilitate smallholder farmer integration and achieving food security in Nigeria. Major contributions are expected from following areas:

i. Finding market opportunities for farmers

Farmers can increase their income by finding market opportunities where they can compete on their skills and quality of product rather than by just offering the lowest price (Macharia et al., 2016; Fearne and Hughes, 1999). AI-enabled platforms can give smallholder farmers the information they need to connect directly to buyers of their produce, reducing food waste and increasing farm income. AI can also help address the market failures by improving traceability to prove the origin and quality of produce, which is needed to secure supply contracts and access markets.

Fodlocker, a Nigerian start-up is using AI to guarantee markets for smallholder farmers and improve procurement efficiencies for large buyers (Alawode, 2019). The company, a foodstuff and grocery aggregator uses deep learning for forecasting demand for farm produce and consumer goods. For farmers, the platform enables access to a fairly-priced, transparent, mobile marketplace. For vendors, the benefit is increased reliability in sourcing high quality produce and for farmers, better returns. Applications can be developed to help farmers with low levels of literacy manage issues with little training required. For example, farmers could upload pictures of infected and diseased crops (using their internet enabled phones), and then get advice or solution to their pest and disease control challenges.

ii. Mitigating food losses

Wasted food, simply defined, is uneaten edible food, largely generated at the consumer level either at or away from home (Stangherlin and de-Barcellos 2018). Food waste epitomizes an unsustainable system of food production and consumption (Martin-Rios et al., 2021). Globally, estimates of annual food losses that occur from farm to fork are as much as one third of annual global food production, or about 1.3 billion tons (FAO 2019). In emerging markets like Nigeria, greater percentages of losses take place: they occur throughout the stages of production, postharvest handling, storage, and processing stages. AI can help by designing systems that prevent edible food from being thrown away (Tavill, 2020).

Digital applications are proving to be a saviour for reducing significant amount of food waste and helping to provide that food to the needy (Tolentino, 2019; Chaturvedi et al., 2020). Frank (2022) presents a simple, low-cost approach, using an electronic learning management system to connect college students with access to desirable food that would otherwise have been wasted. At the national levels, Nigeria can employ the large data gathering and information processing systems based on AI to get insights into the country's annual estimates of food mass flows, including imports, exports, distribution, consumption, surplus food production, and final disposal. Thus the uptake and redistribution of surplus food can be carried out as a potential food waste prevention strategy as it is done in other places (Facchini et al., 2018; Wetherill, 2019).

AI works with data, for example, those produced by different sub-systems that comprise a food supply chain (FSC), such as farms, food industries, distribution centres and retail stores, collected as food product transactions occurrences or by sensor based tools, equipment and fashion solutions across the FSC. For instance, AI in the food supply chain (FSC), along with technologies, such as Industry 4.0, the Internet of Things (IoT), the Global Standards one (GS1) labelling schemes and other emergent technologies, such as blockchain, can provide a basis for integrating the food value chain by sharing FSC transactions via a distributed trustworthy platform. This potentially enables the realisation of the circular food supply chain goals (CFS) (Ramadoss et al., 2018; Valente, 2022).

Already, there are apps managing food usage across industries – foods and beverages, hospitality etc., with a view to minimising wastages. They provide the user with food supply and location knowledge; improve the user's food literacy; and facilitate social food sharing of excess food.

Examples include FoodScan (Sainz-De-Abajo et al., 2020) which is food monitoring app that works by scanning the groceries receipts. Others are Fridge Pal, LeftoverSwap and EatChaFood (Farr-Wharton et al., 2014). Consumers' preference for these apps is generally encouraging (Tribhuvan, 2020). There are also apps that manage food stores and warehouses by real time remote monitoring (through sensors) and predicting storage conditions and suggesting preventive actions (Dey, 2018). Many of these apps can be applied, particularly by big distribution companies, with some cultural modifications, to the Nigerian situation.

iii. Climate Smart agriculture

A critical developmental challenge is that agriculture both contributes to and will be fundamentally affected by climate change. Land use, including deforestation for arable land, and the forestry industry, account for 28 percent of net greenhouse gas emissions, while climate change affects the availability of, access to, and stability of the global food system (Tubiello et al., 2013). The challenge in meeting food demand and transporting food across markets sustainably cannot be solved through business-as-usual farming practices.

Climate-smart agriculture (CSA) is an integrated approach to managing landscapes—cropland, livestock, forests and fisheries--that address the interlinked challenges of food security and climate change (2013; Gulzar et al., 2020). CSA targets three objectives: (i) sustainably increasing agricultural productivity to support equitable increases in farm incomes, food security, and development; (ii) adapting and building resilience of food systems to climate change; and (iii) reducing greenhouse (GHG) emissions from agriculture (Kurgat et al., 2020). Interventions ranging from climate information services to field management have potential to achieve these goals (Khatri-Chhetri et al., 2016; Nyasimi et al., 2017).

There is a need for policies, infrastructures and considerable investments to build the financial and technical capacity of farmers (especially small holders) to enable them to generate economic rural growth and ensure food security. First, there is a need for diversified cropping systems in view of climate related risks. AI, using weather data and other metrics such as market information can assist in decision of what crops or animals to raise. There is a need to develop a crop insurance scheme which makes it different from earlier schemes: farmers' data is correctly captured the insurance firms can have information such as the GIS-derived locations of such farms. AI can also come in to ensure that the government assisted input supply schemes – e.g. supply of fertilizers, farm chemicals, tractor services, is transparent.

iv. Extending products and services to underserved farmers.

AI can be leveraged to deliver targeted, personalized and relevant insights and recommendations to farmers (Cook and O'Neill, 2020, Bicksler et al., 2022). Many Nigerian farmers lack access to affordable financial products because of the significant time and cost required to price their risk and collateral, as well as the difficulty of serving farmers in rural and remote areas. Technological advancements in satellite weather data collection and the wider adoption of mobile technology can dramatically reduce these costs, facilitating the extension of financial products to farmers (Mhlanga, 2021).

Machine learning platforms are increasingly being employed by lenders to generate credit scores to help farmers access the microloans and insurance needed to upgrade their inputs to production, and this includes farmers without traditional collateral or bank accounts (Kumar et al., 2021).

Apps can be created and platforms set up to allow farmers to upload photos of crops and pests or disease, which are processed alongside satellite, geospatial, and other data sources, to estimate a farmer's collateral or to make estimates of the farmer's individual financial health and creditworthiness (Chandra and Collis, 2021; Kumarathunga et al., 2022).

5. CHALLENGES TO AI IMPLEMENTATION IN NIGERIA

Although AI implementation varies across nations, it is still in the initial phase in developing countries such as Nigeria (Sharma et al., 2021). Challenges such as data quality, privacy and lack of skilled workforce limit the scope of AI implementation in emerging economies, especially in agriculture. Farmers tend to perceive AI as something that applies only to the digital world. They might not see how it can help them work the physical land. Their resistance may be caused by a lack of understanding of the practical application of AI tools. New technologies often seem confusing and unreasonably expensive because solution providers fail to clearly explain why their solutions are useful and how exactly they should be implemented. Although AI can be useful, there is still a lot of work to be done by technology providers to help farmers implement it the right way. Some serious constraints readily can be highlighted:

i.) **Inadequate Technology Infrastructures:**

AI requires a proper technology infrastructure for it to work. Unlike acquiring a tractor, AI is not something tangible but a set of technologies that are automated through programming. It needs other technology to actually work. In other words, to reap all the benefits of AI, farmers first need a technology infrastructure. Farmers need to understand that AI is only an advanced part of simpler technologies for processing, gathering, and monitoring field data. One of the critical requirements for the application of AI and related IT technologies to any nation's economic sectors is power supply. Nigeria has power supply deficits, about 80% of the population still does not have access to on-grid electricity. Equally critical is internet connectivity. According to the World Economic Forum (World Economic Forum, 2020) internet users stand at 25.7% of the population (ranked 107th out of 140 countries in 2019). However, the country set its own target of connecting 30% of the population to broadband, reaching 33% in early 2019, representing 65 million citizens. A new target of 70% has been set by the Federal Government for 2024 (Osuagwu and Elebeke, 2019).

ii.) **Lack of experience with emerging technologies:**

It may be hard to sell the technology in areas where agricultural technology is not common. Farmers will most likely need help adopting it. Perhaps, the most important condition for rapid adoption of AI technologies and reaping the associated rewards is a well-educated and motivated workforce with the right skills. There should therefore be improved efforts to improve of literacy in general, and computer literacy in particular.

iii.) **Privacy and security issues:**

Since there are no clear policies and regulations around the use of AI, not just in agriculture but in general, precision agriculture and smart farming raises various legal issues that often remain unanswered. Privacy and security threats like cyber-attacks and data leaks may cause farmers serious problems. Unfortunately, many farms are vulnerable to these threats. The Nigeria Digital Agriculture Strategy 2020-2030 (NITDA, 2020) is a welcome development. It is hoped that there will be commitments to its implementation and efforts should be made to address these challenges.

iv.) **Manpower for AI development:**

AI is an emerging technology, there are few who possess the skills or training necessary for AI development. In rural areas, the basic issues is lack of digital skills as many people are illiterate. This is made more difficult by a mismatch of skills and a 'brain drain' of highly-skilled people to other countries. With talent being one of the biggest challenges to AI, it not surprising that companies and countries are leaving no stone unturned when sourcing people and skills.

v.) **Legal Issues:**

One of the newest challenges of AI include the recent legal concerns being raised that organizations need to be wary of AI. If AI is collecting sensitive data, it might be in violation of state or federal laws, even if the information is not harmless by itself but sensitive when collected together. Legal and ethical issues of AI which Nigeria should plan for include privacy and surveillance breeches together with introducing bias and discrimination into decision making. Express policies are needed that will meet up with the technologies emerging under the fourth industrial revolution.

6. CONCLUSIONS

AI has become pervasive in today's world, therefore, the working knowledge of this technology is required to stay relevant in most fields, agriculture inclusive. The present review provided a comprehensive understanding of AI and intelligent methodologies which can be employed to tackle several challenges in agriculture based businesses. Additionally, the paper focused on the ideas of applying AI to Nigeria's agriculture, considering the opportunities and possible challenges. AI-powered solutions have been applied in areas such as farm, crops and animal monitoring, diseases and pest detection, intelligent farm chemicals application, automatic weeding, aerial survey and mapping, smart irrigation, intelligent produce grading and sorting, among others. Obstacles of inadequate technology infrastructure such as broadband internet access, and paucity of a workforce with the right skills exist in Nigeria were identified. Nigeria must, with continuous efforts, overcome these challenges if the country hopes to be competitive in her agriculture.

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