

An Overview of Machine and Deep Learning Technologies Application in Agriculture: Opportunities and Challenges in Nigeria

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Abstract

Globally agriculture has remained a key factor in food security, employment, and several other favorable economic indices. However, factors like rising world population, trade globalization, and climate variabilities have created the need for modernization and optimization to boost production and livelihood. Machine learning allows machines to read from a pool of available data and provide data-centric results. This has opened up a new and promising perspective. The paper examines recent proven works in machine learning technology application in agriculture to establish the modest contribution of machine learning and emerging deep learning technologies in this field to highlight the need for its adoption in the Nigerian agricultural ecosystem. Therefore, a systematic review was carried out using a categorization model of key agricultural subsectors/activities. Findings have shown a widespread of its application with significant positive impact in almost every aspect of agriculture with new works showing higher result efficiency in deep learning technologies application. Insightful recommendation from these technologies has proven capable of boosting agriculture on various fronts. Thus, the adoption of ML/DL technologies in Nigeria's agriculture will go a long way in helping the country attain food sufficiency.

Keywords: *e-Agriculture, Artificial Intelligence, Machine Learning, Deep Learning*

1. Introduction

Agriculture in Nigeria could be designated as one of the mainstays of the economy as it does not just provide food to its teeming population but also accounts for a sizeable percentage of its employment. Agriculture has since adopted the use of technology based on the Agriculture 4.0 framework (Anderl, 2015). This has gained momentum due to rapid advancement in high-performance computing, the availability of big data, the semantic web, and IoT. One of such technologies that are making a significant contribution to agriculture is the field of Artificial intelligence (AI). This entails the use of systems capable of learning from a dataset and making intelligent decisions on their own. This concept of artificial intelligence is called *Machine Learning* (ML) and its emerging subdomain of *Deep Learning* has proven capable of providing 'unbiased' data-centric results. The performance of these models and algorithms can be measured using various mathematical and statistical models. This has increased its acceptability thus, its growing application to almost every genre of human endeavor from medicine to aviation to marketing and so on (Immaculate et al., 2020).

Food and Agriculture are essential to the sustainability of every society and Nigeria is no exception. Pressure on agriculture and the agricultural system will continue to increase due to the exponential expansion of the human population. To this end, many kinds of research are ongoing in the diverse field of Agriculture from crop production to soil management, marketing, etc. both globally and locally. Some of these researches involve the use of Machine learning technologies to boost these specific agriculture areas. However, in Nigeria farming is still

mostly done manually, and farmers are reluctant to adopt advanced technologies in farming either due to lack of knowledge, heavy cost, or because they are unaware of the advantages of these technologies. Consequently, denying them of this huge potential. In this paper, we present an overview of applications of Machine Learning and Deep Learning technologies in Agriculture. We also highlight opportunities therein and the potentials and challenges, particularly in Nigeria.

1.1 Machine Learning Vs Deep Learning

According to (IBM, 2021) machine learning is a branch of artificial intelligence (AI) that focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy. It is an intersection of computer science and statistics where algorithms are used to perform a specific task without being explicitly programmed; instead, they recognize patterns in the data and make predictions once new data arrives. The learning process of the algorithm could be supervised or unsupervised.

Deep Learning is a subset of machine learning that uses a mathematically complex multi-layered artificial neural network structure to analyze data and draw conclusions similar to how a human brain works. This process has led to a process of learning that is far more capable than that of standard machine learning models. Figure 1. Depicts a diagrammatic structure of ML and DL in the Artificial Intelligence domain.

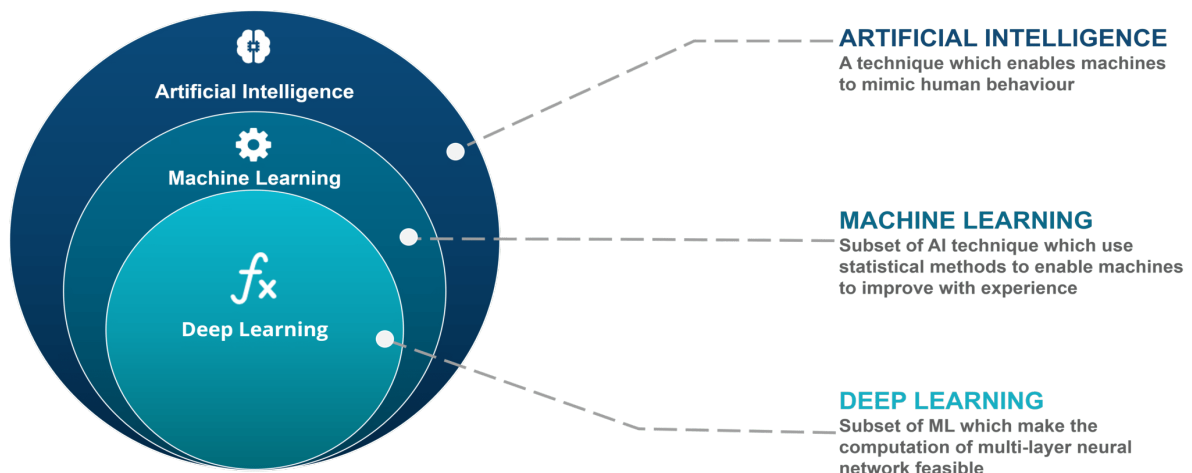


Figure 1: Relational structure of ML and DL (Source: [Edureka, 2018](#))

2. Related Works

At the inception of our project, we understudy recent literature in the area of interest. Liakos et al., (2018) in their published review paper on the application of machine learning in the agricultural sector. They based their analysis on publications focusing on crop management, livestock management, water management, and soil management. While van Klompenburg et al., (2020) conducted a systematic review on the application of machine learning in crop yield prediction. Meshram et al., (2021) in their published article titled “Machine learning in agriculture domain: A state-of-art survey” they did an extensive survey of the latest machine learning application in agriculture they focused on pre-harvesting, harvesting, and post-harvesting. Consequent to the reviewed literature, our work provides an updated systematic review on the subject and considers a broader aspect of its application in agriculture. We also captured works using deep learning techniques.

3. Methodology

3.1. Review Protocol

To carry out the systematic review we adopted standard review guidelines as provided by Kitchenham & Brereton, (2013).

1. The research questions are defined.
2. Outline databases to be searched for relevant and proven studies. The databases that were used in this study are Science Direct, Researchgate, and Google Scholar.
3. They were filtered and assessed using a set of exclusion and quality criteria.
4. At the first level, using the generic classification (Liakos et al., 2018). we categorized articles, in their appropriate area of coverage in the classification table i.e. Crop management, livestock management, water management, and soil management.
5. Finally, all other relevant data from the selected studies are extracted, and eventually, the extracted data were synthesized in response to the research questions;

3.2. Research Question

To properly achieve our review study. We define the following research questions(RQs).

- RQ1- Which of the AI techniques between machine learning and Deep learning is most used?
- RQ2- Which model/algorithm of Machine learning and/or deep learning is used?
- RQ3- Which areas of agriculture are machine learning and deep learning most applied?
- RQ4-What is the evaluation result?
- RQ5- What are the challenges in the application of machine learning and/or deep learning in agriculture from the literature?

3.3. Search Strategy

The initial search was carried out in the outlined databases “machine learning” AND “Agriculture”. Articles were retrieved, and abstracts were read to ensure consistency with the research field and also keywords searched.

A second search was done with the keywords “deep learning” AND “Agriculture” articles were also processed. Then finally a search was carried out with the keywords “Machine learning” OR “Deep learning” + “Application in Agriculture”. This was done across all the outline databases to ensure as many articles as possible were captured. Thereafter we apply the exclusion criteria. This brought us down to 249 studies.

3.4. Exclusion criteria

For us to ensure only relevant and qualitative studies are extracted. We set up a filtering mechanism with the following eight (8) exclusion criteria.

Exclusion criteria 1 - Publication is not related to the agricultural sector combined with machine learning and/or deep learning.

Exclusion criteria 2 – Publication is outside of the scope of four (4) key agricultural areas of interest i.e. crop management, livestock management, etc.

Exclusion criteria 3 – Publication is not written in English

Exclusion criteria 4 – Publication that is a duplicate or already retrieved from another database.

Exclusion criteria 5 – Full text of the publication is not available.

Exclusion criteria 6 – Publication not a peer-review Journal.

Exclusion criteria 7 – Publication is a review/survey paper.

Exclusion criteria 8 – Publication has been published before 2012.

Sequel to the application of the exclusion criteria. We were able to come up with a total of 31 articles. Figure 2 shows the distribution of articles from source databases.

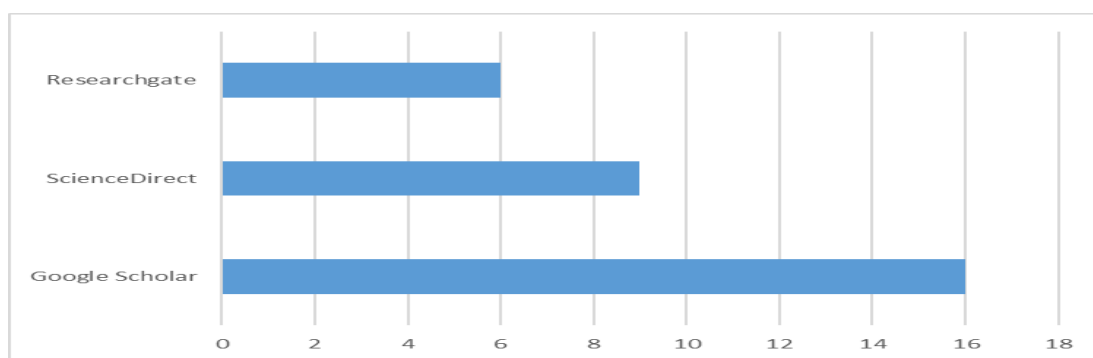


Figure 2. Distribution of Articles from Source Databases

4. Results

The selected articles were fully read and carefully processed to achieve the review objectives. Tables 1 to 4 show articles for each of the research generic classifications i.e. Crop Management, Livestock Management, water, and Soil Management respectively. While Figure 3 shows the proportion of Machine learning to Deep Learning applications in Agriculture. Figure 4 and 5 shows the count of ML and DL models and algorithms used respectively. Figure 6 shows the distribution of works based on the adopted classification.

Table 1. Articles Related to Crop Management

Article	Function	Technology	Model/Algorithm	% of Result Accuracy
(Zhang et al., 2017)	Quality detection	ML	SVM	95
(Sabzi & Abbaspour-Gilandeh, 2018)	Weed detection (Classification)	ML	ANN	98.1
(Maione et al., 2016)	Quality detection	ML	EL/RF	93.8
(Pantazi et al., 2017)	Disease identification	ML	ANN-XY	95
(Chung et al., 2016)	Disease detection	ML	SVM	88
(Su et al., 2017)	Yield Prediction	ML	SVM	82
(H. Wu et al., 2019)	Disease Detection	DL	CNN	94.1

(Hu et al., 2017)	Crop Quality	ML	SVM	93.3
(Grinblat et al., 2016)	Species recognition	DL	CNN	90.9 to 98.2
(Pantazi et al., 2016)	Weed detection	ML	Hybrid(ANN, Clustering)	92 to 100
(Linker, 2018)	Yield Prediction	ML	MLR	85
(Y. Chen et al., 2019)	Yield Prediction	DL	CNN	92
(Ferentinos, 2018)	Disease Detection	DL	CNN	99
(Chavan & Nandedkar, 2018)	Weed Detection	DL	CNN	98.2
(Zhou et al., 2019)	Species recognition	ML	Hybrid(LSMT,RF,SVM)	83.7

Table 2. Articles Related to Livestock Management

Article	Function	Technology	Model/Algorithm	% of Result Accuracy
(Dutta et al., 2015)	Animal Welfare	ML	EL/Bagging+ Tree Learner	96
(Rahman et al., 2018)	Livestock Production	ML	RF	91
(Morales et al., 2016)	Livestock Production	ML	SVM	96
(Hansen et al., 2018)	Livestock production	DL	CNN	96
(Yang et al., 2018)	Animal welfare	DL	CNN	98

Table 3. Articles Related to Water Management

Article	Function	Technology	Model/Algorithm	% of Result Accuracy
(Mehdizadeh et al., 2017)	Evapotranspiration	ML	Hybrid(Regression, MARS)	82
(Patil & Deka, 2016)	Evapotranspiration	ML	ANN	78
(Mohammadi et al., 2015)	Prediction of daily Dew	ML	ANN	82
(H. Chen et al., 2020)	Water quality	DL	CNN	91
(Li et al., 2020)	Soil water content	DL	FFNN	94
(Lee et al., 2020)	Water quality	ML	DT	87

Table 4. Articles Related to Soil Management

Article	Function	Technology	Model/Algorithm	% of Result Accuracy
(Coopersmith et al., 2014)	Soil drying	ML	Hybrid (ANN, BP)	91
(Johann et al., 2016)	Soil Moisture (Estimation)	ML	ANN	82
(Padarian et al., 2019)	Soil properties (Estimation)	DL	CNN	90
(Chakraborty et al., 2020)	Soil Erosion	ML	Hybrid (GWR,ANN)	91
(T. Wu et al., 2019)	Soil Properties (organic Matter)	DL	Hybrid(CNN,RF, XGBoost)	94

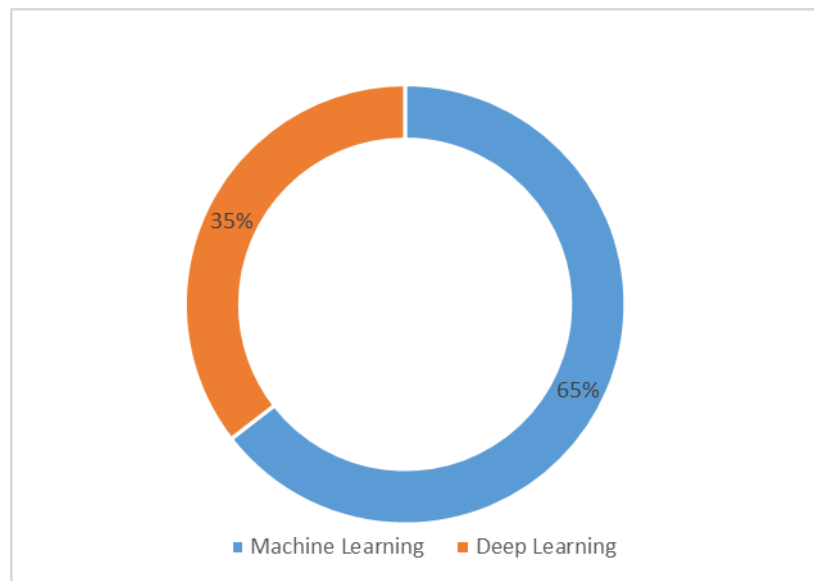


Figure 3. The proportion of ML to DL Application in Agriculture

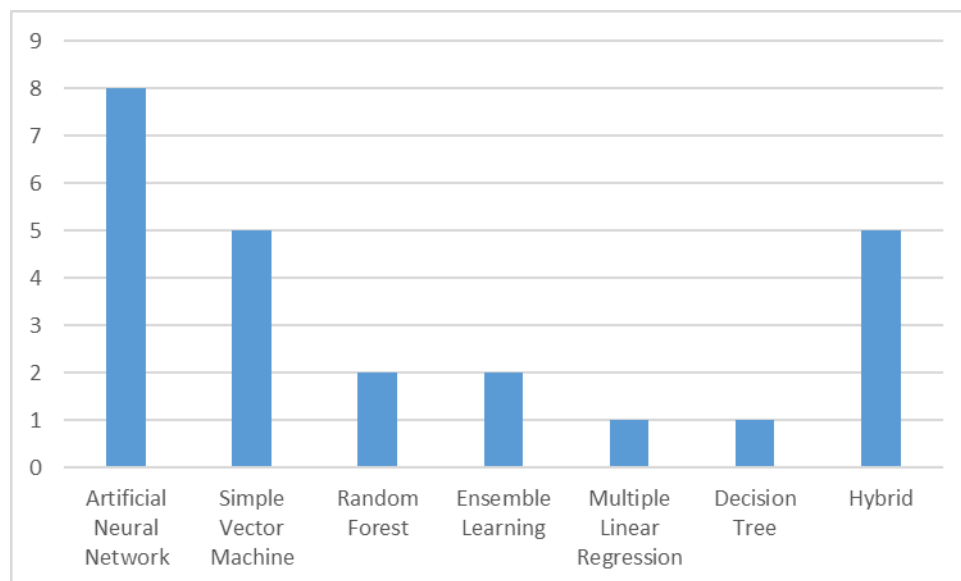


Figure 4. Count of ML Models/Algorithms

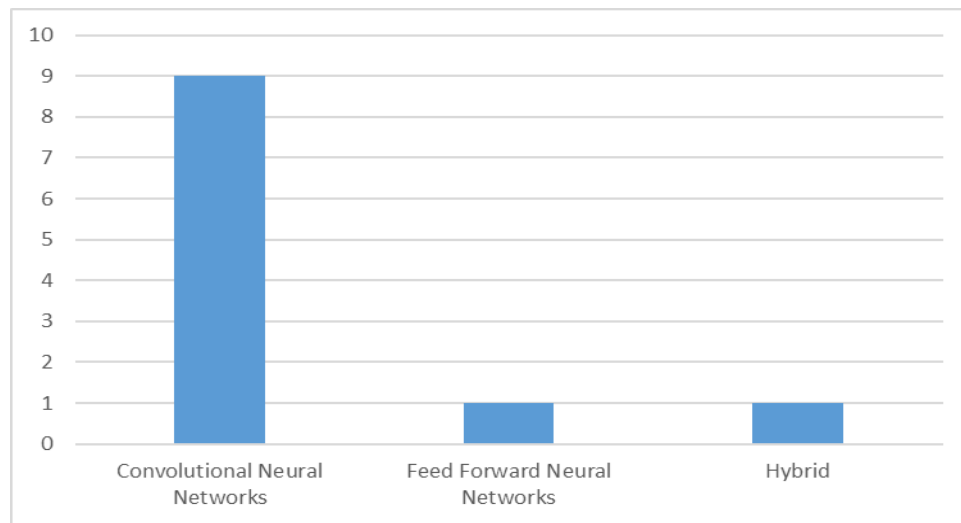


Figure 5. Count of DL Models/Algorithms

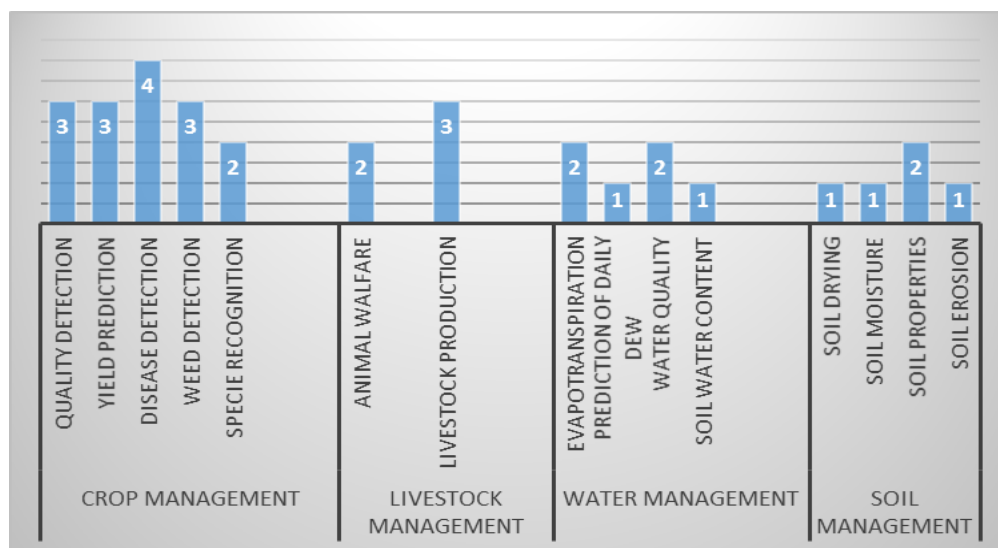


Figure 6. Distribution of Works Based on Adopted Classification

5. Discussion

Going by the results from the review. Even from our limited sample population, it can be deduced that traditional ML-based application is most used in agriculture though this is expected due to the relative infancy of deep learning technology to machine learning. The crop disease detection unit has the highest with 4 articles while the crop management subsection has the most articles at 16.

Artificial Neural Network(ANN) is the most used for Machine learning applications while Convolutional Neural Network (CNN) is most used for Deep learning applications. Analysis of results achieved across the entire survey has shown that both ML and DP-based applications have an average of 84% and 91% result accuracy respectively.

However, it was observed that different result estimation evaluation parameters and benchmarking techniques were used by each author even those that used the same ML or DL algorithm. This could be an area of further research, so we can better understand how best to evaluate result estimates for the various ML and DL models.

Consequently, these results have shown that ML/DL technologies are making a significant impact in agriculture. Therefore, any country that is desirous of improving its agriculture will be unwise to ignore it.

In Nigeria agriculture has remained one of the drivers of the economy, contributing 26% to its Gross Domestic Product (GDP) in 2019. Taking 66% of its total labor force, consisting mainly of smallholder farmers (Raithatha, 2020). According to a statistical report, Nigeria has a population of over 200 million with over 60% within the productive age bracket of 18-60 years and about 30.2 hectares of arable land (Data Commons, 2018).

Additionally, below are carefully identified opportunities and potentials for ML/DL techs in Nigeria Agriculture to scale up:

5.1 Opportunities

- i. Agriculture currently is receiving tremendous attention in the country. With numerous funding support initiatives through CBN, BOI, etc. such as:
 - a) The anchor borrowers scheme was created to provide linkage between anchor companies involved in the processing and smallholder farmers (SHFs) of the required key agricultural commodities. The program thrust is the provision of farm inputs in kind and cash (for farm labor) to smallholder farmers to boost production of these commodities and stabilize inputs supply to agro-processors.
 - b) NIRSAL: is a risk-sharing arrangement/guarantee for Agro-related lending with finance houses that aim at encouraging banks and other financial institutions to avail loans to agro-based projects.
 - c) AGSMEIS: this is another government developmental loan scheme with single-digit interest and a longer tenor for Micro, Small, and medium enterprise (MSME) in Agro and Agro related ventures.
 - d) BOI: Bank of Industry is a government development bank that also provides funding to start up's and existing MSMEs in the country.

So farmers, Agritech companies, and other value-chain players can easily get funds to actualize their projects.

- ii. NITDA Grants: National Information Technology Development Agency (NITDA) provides a grant to start-up tech entrepreneurs through its Incubation program designed to scale up ideas to market.
- iii. A large percentage of the youth population. According to ICTWorks youths are most likely to adopt new technology than the elderly (ICTWorks, 2021).
- iv. Government willingness to design policies/programs to adopt 'safe' new ICT technologies for Agric. such as:
 - a) e-Agriculture Portal Project: This is a partnership between the Federal Ministry of Agriculture and Rural Development (FMARD) and NITDA to among other things showcase the essential features and key aspects of the food and agriculture industry in Nigeria.

- b) National Farmers Helpline is a contact center designed to allow farmers and other agro value-chain players to access advisory services via phones and selected other e-channels. This is supported by FMARD/National Agricultural Extension and Research Liaison Service (NAERLS).
- c) NAVSA: which stands for National Adopted Village for Smart Agriculture is a NITDA digital platform designed to practically enable and accelerate the achievement of Government (Federal, State, and local) policy drives in agriculture.

5.2 Potentials

Using ML data-driven techniques will provide new insights, that could ultimately lead to:

- i. **Better yield for both Crop and livestock.:** Achievable through accurate disease diagnosis and management, location-specific soil analysis, and improved seed variety analysis.
- ii. **Improved linkages along the value chain:** This is achieved through ease of integration of the various actors from input, farmers, finance, and extension agent to market
- iii. **Reduction in production cost.:** a more insightful cost-effective technique is applied in every step of the production. E.g. for the crop; from Land preparation to planting, weeding, fertilizer application, and harvesting.
- iv. **A Path to Sustainability and Self-sufficiency in Agriculture:** High-profit margins will lead to more production and increased farming participation thus, creating a self-sufficient nation in agricultural produce that will continue to cater to the nation's growing population.
- v. **Increased agriculture contribution to the nation's GDP:** Occasioned by the increase in production, employment, and newly spring up MSMEs in Agrotech, Agro-processor, etc.
- vi. **Global leadership in ML technology advancement:** With the adoption of ML technologies in Nigeria agriculture. This will lead to more local research, and ML idea incubation labs capable of propelling the country to the forefront of ML advancement in the world.

5.3 Challenges

Despite the enormous advantages inherent in the use of machine learning applications in Nigeria's Agriculture, myriads of challenges constitute a stumbling block to its achievement. These challenges can be classified as personnel, infrastructural and technical. They include:

- i. **Unavailability of Enough and Quality Dataset:** the two basic factors that can affect the effectiveness of any machine learning application are *bad algorithms*, *bad data*, or a combination of both. Early ML and DL application developers for Nigerian Agriculture will have a problem with the availability of enough and/or poor quality datasets to train and feed their algorithm due to the infancy of the technology in Nigeria. Thus, they might have to create their data, which might likely lead to *overfitting*.
- ii. **Poor Infrastructure:** The telecommunication and electricity infrastructure in Nigeria is lacking or is poorly developed in rural areas where most Agricultural practice is performed. These infrastructures should serve as a prerequisite to many of the modern ICTs for optimum performance and achieving the desired objectives. Though satellite and wireless technologies are now in use in Nigeria, they are largely developed around urban cities, and even here, the infrastructure is often

- inadequate. There are problems with low bandwidth and there is a need for strengthening the Internet backbone.
- iii. **High Rate of Illiteracy in Rural Areas:** Literacy is a fundamental barrier to participation in knowledge societies. A large proportion of the rural population of Nigeria, the majority of who are women, is illiterate, and most pictographic and audio-visual information usually has some text that goes with it. This means that these individuals are disadvantaged and lack the basic skills required to harness the benefits of ML technologies. The assistance of intermediaries such as extension agents may thus be required.
 - iv. **Privacy and Security Issue:** 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 raise various legal issues that often remain unanswered. Privacy and security threats like cyberattacks and data leaks may cause farmers serious problems. Unfortunately, many farms are vulnerable to these threats.

6. Conclusions

We conducted a systematic review of Machine and Deep Learning technologies application in Agriculture to ascertain their suitability and efficacy in moving agriculture forward. The result has shown a very positive and significant impact. We also identified the potentials, opportunities, and challenges for the adoption and/or deployment of these technologies in Nigeria.

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