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Artificial Intelligence in Sustainable Crop Production: A Review of Digital Transformation in Agriculture

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ABSTRACT

Global agricultural systems face significant pressure to improve productivity and ensure sustainability in light of climate variability, degradation of soil, and the anticipated rise in world population to approximately ten billion in the next 25 years. This analysis looks at how artificial intelligence (AI) might improve sustainable grain production, with a focus on poor nations, especially those in Africa. AI-driven advancements in crop breeding, irrigation control, and pest management are included in the scope, along with how they complement the objectives of Climate Smart Agriculture (CSA). The review, which focuses on earlier research, finds that AI technologies are essential for enhancing resource allocation, decision making, and overall farm productivity. It also highlights certain challenges affecting the way of general acceptance. Among these difficulties include issues with infrastructure, small levels of digital literacy, inadequate data, alongside inadequate policy backing. The results highlight the significance of creating inclusive, localized AI models that are adapted to socioeconomic and agro-ecological circumstances. According to this analysis, AI has a lot of potential to improve sustainable food production, but its application requires an integrated policy framework and capacity building. To guarantee fair and long-lasting AI integration throughout agricultural systems, future research should concentrate on scaling sensitive solutions, improving data ecosystems, and promoting multi-stakeholder collaboration.

Keywords: *Artificial Intelligence, Sustainable Agriculture, Crop Production, Digital Transformation, Precision Agriculture*

1.0 Introduction

The total population of the world is expected to reach over ten billion in the next 25 years (2050), increasing farming production in a state of moderate financial development by roughly 50% from 2013 (FAO, 2017). At the moment, about 40% of the land is used for crop cultivation. Farming contributes significantly to the national GDP and job creation. It is not only actively participates in the economies of emerging countries but also contributes substantially to the thriving of established nations. Agricultural augmentation has led to a significant increase in the per capita income of the rural region, so it will be counterproductive and logical to give the agricultural industry more attention. In countries like India, the agricultural industry accounts for 50% of the total workforce and 18% of GDP. Development related to agriculture will promote communal development, which will consequently lead to transition in rural communities and, consequently, structural shifts (Mogili and Deepak, 2018; Shah et al., 2019). Since the advent of technology, many industries have undergone significant change (Kakkad et al., 2019). Agricultural industry, although the least digitalized, has surprisingly seen an improvement in the evolution and adoption of smart farming. Artificial intelligence has started to play an important part in our everyday activities, with the potential to change our surroundings and expand our perceptions (Kundalia et al., 2020; Gandhi et al., 2020; Ahir et al., 2020). Plessen (2019) introduced an agricultural organizing technique that combines truck route with crop assignment. The workforce, previously limited to a minor industrial sector, is now chipping in to several industries due to these emerging innovations. Agricultural operations comprise a variety of jobs, including choosing fertilizer, controlling irrigation, evaluating soil health, and making decisions related to crops. Two machine learning methods that are very good at handling large volumes of multidimensional data are neural networks and random forests (Niazian and Niedbała, 2020). These methods enhance genotype classification, yield prediction, and in vitro breeding optimization. Combining machine learning with images enables precision phenotyping, which enhances future research on plant breeding and precision farming. This change entails using methods that boost agricultural productivity while protecting the environment and guaranteeing the well-being of farming communities. Increased soil health, better management of water, and more resistance to climatic variability are all possible outcomes of sustainable agriculture practices in Nigeria (Ojo et al., 2021). Additionally, by creating jobs, improving rural livelihoods, and lowering poverty, sustainable agriculture can support economic growth (Adesina et al., 2020). Therefore, attaining sustainability goals in agricultural production requires the introduction of advanced technologies like artificial intelligence (AI). Technologies related to artificial intelligence have become extremely potent instruments that have the ability to transform contemporary farming methods. Crop monitoring systems, autonomous machinery, smart farming, and predictive analytics for yield forecasting are a few examples of AI uses in farming (Wolfert et al., 2017). Smart farming, for example, applies Artificial Intelligence to evaluate data from multiple sources so that farmers may make well-informed decisions about crop health monitoring, control of pests, and resource allocation (Kamilaris & Prenafeta-Boldú, 2018). Furthermore, by automating labor-intensive jobs and raising overall output, AI-driven systems can improve agricultural operations' efficiency (Zhang, 2022; Sullivan et al., 2020).

Statement of the Problem

Inadequate water management, temperature swings, mineral concentration, food insecurity and waste, and many other issues are major problems for agriculture. Digital agriculture is significantly impacted by the acceptance of various cognitive solutions. Even though there is still a lot of research being done and some are currently available for use, the manufacturing sector is currently terribly dispossessed (Shobila and Mood, 2014). When it comes to solving the real-world issues that farmers face and using forecasting and autonomous decision-making methods to resolve them, farming is still in its infancy. To fully realize the huge potential of AI in agriculture, applications need to be more dependable. Only then will they be able to use the right structure for efficiently collecting contextual data, managing rapid shifts in external factors, and supporting real-time decision making (Slaughter et al., 2008).

Regarding agricultural intelligence in sustainable crop production, there are still certain issues, nonetheless. Among them are:

1. AI technologies are not widely used in agriculture.

2. The issue of sustainability in the environment

3. Ethical and policy barriers in the development of AI

4. Insufficient agriculture data quality and availability for appropriate AI application

Objectives of the Review

Examining how artificial intelligence can be applied to achieve sustainable crop production is the main goal of this review. The specific goals are:

1. To assess how artificial intelligence is currently being used in agricultural production

2. To evaluate the adaptability of AI solutions to certain agro-ecological zones or locations.

3. To examine ethical, legal, and policy issues surrounding the application of AI to agricultural productivity.

4. To determine the main obstacles impeding the uptake and efficiency of AI technologies.

The following review questions resulted from these goals:

1. What uses does artificial intelligence now have in crop production, and how does it support sustainable farming methods?

2. How much do AI solutions in various farming systems adapt to local agro-ecological conditions?

3. What ethical, legal, and policy concerns surround the use of AI in agricultural production?

4. What are the main challenges to farmers' successful acceptance and application of AI technologies in crop production?

Scope and Structure of the Review

Beginning with an introduction, this review paper is organized into ten distinct sections: history, problem statement and relevance, aims, review questions, and paper structure. The methodology, which includes the review type, data sources and search strategy, inclusion and exclusion criteria, screening and selection procedure, and analysis, categorization approach, comes after the introduction. The third is the conceptual framework, which includes the context of digital transformation, artificial intelligence in agriculture, and sustainable agricultural production. Applications of AI in sustainable crop production will be covered in the fourth section. The benefits and impacts theme analysis comes next. Case studies are followed by the difficulties and obstacles, and finally, the conclusion, future prospects, and references.

2.0 Conceptual Framework

Sustainable Crop Production

Crop production that doesn't destructively affect the environment, living organisms, or crop quality is referred to as sustainable crop production. Growing crops in a sustainable manner improves the system's capacity to sustain a long-term, constant range of production of food production and quality without raising the need for chemical fertilizers to regulate the system. Maintaining soil organic matter, reducing the use of pesticides and implementing integrated pest control, preserving living organisms, guaranteeing the safety of food and quality, enhancing nutritional quality, and enriching the soil with organic fertilizers are all aspects of sustainable crop production. It can also be defined as the agricultural production that does not negatively impact biodiversity, the environment, or the quality of agricultural crops. Growing crops sustainably improves the system's capacity to sustain long-term, steady levels of food supply and quality without raising the need for and demand for agricultural chemical inputs to regulate Plant production methods have a site-specific application in this integrated system, which offers long-term advantages. In addition to meeting human requirements for food and fiber, sustainable crop production improves the environment and natural resources (Gold 2009). Organic farming is regarded as a strategy that will eventually improve the environment by being sustainable. This agricultural strategy will play a significant role in ensuring food security. To improve sustainable production systems, a gradual transition from conventional to organic agriculture is required (Azadi et al., 2011). In order to create a sustainable agricultural production system that makes use of internal resources, farmers must cultivate crops in a specific order. In order to create a sustainable agricultural production system that makes use of internal resources, farmers must cultivate crops in a specific order. When internal resources—such as crop combination, nutrient cycling, and soil water—have a greater impact on final production than external resources—such as weather—a sustainable system will be attained. Utilizing synergism and minimizing potential conflicts between planted crops and harvested crop residues can increase the yield and quality of agricultural crops (Tanaka et al. 2007). Maintaining soil nitrogen levels is crucial for the sustained production of crops like wheat. To achieve this, a crop rotation strategy is used, in which mung beans and wheat plants alternate. It was found that the concentration of nitrogen in the soil rose throughout the mung bean growth period, and that wheat used this increased nitrogen during its growth. The amount of nitrogen in the soil was further raised by the application of organic fertilizers. Crop rotation techniques can be used to improve nitrogen concentrations in low-nitrogen soils in a sustainable system (Bakht et al., 2009).

Artificial Intelligence in Agriculture

By offering instruments for automated decision-making, predictive analytics, and real-time monitoring, emerging AI technologies are completely changing agricultural practices. Drones, computer vision, machine learning, and other technologies are being used more and more to improve farming operations. For example, AI systems can evaluate information from satellite imaging, weather forecasts, and soil sensors to establish the best times for planting and effectively control irrigation (Kumar et al., 2022). AI-driven precision agriculture can greatly increase agricultural yields while lowering resource waste, according to a study by Adebayo et al. (2023). By reducing farming's negative environmental effects, AI integration in agriculture not only increases productivity but also encourages sustainable practices. AI systems, for instance, are able to forecast pest outbreaks, enabling prompt actions to lessen the need for dangerous pesticides (Singh et al., 2021).

3.0 Methodology

Review Type

Because the topic is wide and the review type is intended to map out current research, identify major themes, expose gaps, and offer strategic insights rather than statistically analyzed findings, it can be classified as a scoping review. It supports a variety of research formats, such as conceptual papers and case studies.

Data Sources and Search Strategy

The materials analyzed in this review were obtained primarily from different peer-reviewed journals, review papers, conference proceedings, and other relevant research works that directly addressed the focus of this study all of which were from reputable and credible academic databases, including Google Scholar, Researchgate, MDPI, Science Direct, Springer, and JOBASR. The reviewed papers were either available as open-access (free to readers) or subscription-based access (available only to subscribers); this was done to ensure a comprehensive and exhaustive approach to the available information, as it concerned my search focus, an approach that provided a balanced perspective across the spectrum of current research. Key words like “Artificial Intelligence”, “Machine learning”, “Sustainable Agriculture” and "Digital transformation" were used to make the papers more specific and focus on my review topic.

Inclusion and Exclusion criterion

Particular inclusion and exclusion criteria were developed in order to guarantee the quality and applicability of the examined material. The following requirements, listed in Table 1, had to be fulfilled by the studies that were either included or eliminated from the review.

Table 1: Inclusion and exclusion criteria table

Inclusion Criteria	Exclusion Criteria
It has to concentrate on how AI is being used in farming, particularly in agricultural productivity.	Studies that had nothing to do with AI or agriculture were disqualified.
Articles, conference proceedings, or reliable sources from the last ten years must be reviewed.	To preserve the integrity of the review, literature that was not rigorous or adequately examined was also disregarded.
It must be focused on both AI and sustainable crop production	Literature that focused on AI alone were excluded

Screening and Selection Process

The screening and selection process in a scoping review is the methodical procedure used to find, sort, and choose the most reliable and pertinent research to be included in the final review. It is an essential component that guarantees the review's transparency and reproducibility. The first screening was carried out by conducting a direct Google search for the review topic. Reading the paper titles and abstracts was the next step in this procedure. Using the inclusion and exclusion criteria, the ones that weren't relevant were removed. The articles were downloaded, and their whole texts were read as part of the second step, full-text screening. Strict adherence to the inclusion and exclusion criteria led to decisions regarding which papers would be included in the final analysis. These two actions were used to guarantee that only excellent, pertinent works that were reputable in academic reviews were included.

4.0 Discussion

Table 2: Overview of Research on Artificial Intelligence in Sustainable Farming

Author(s)	**Approach Adopted**	**Strength(s)**	**Weakness(es)**
Odirichukwu (2024)	IoT systems powered by AI for managing air quality	Highlights the groundbreaking capabilities of artificial intelligence in resolving environmental problems.	Insufficient emphasis on applications unique to agriculture
Poronakie	AI addressing national issues like insecurity	Demonstrates AI's adaptability to various critical socio-economic challenges	Does not provide empirical evidence for agricultural applications
Umar et al. (2022)	Machine learning for agricultural productivity	Shows AI's effectiveness in enhancing food sufficiency and crop yield prediction	High dependency on data quality, which may be challenging in Nigeria
Elijah et al.(2017)	Internet of Things and data analytics for smart agriculture	Provides practical insights into how IoT enhances food security and export quality	Accessibility issues for small-scale farmers in rural areas
Abdullahi and Sheriff (2017)	Image analysis and fuzzy classification	Demonstrates feasibility of precision agriculture in maize farming	Focused on one crop, limiting scalability
Adekunle (2013)	Precision Agriculture	Explores applicability of AI to improve soil type, crop selection, and disease detection	Limited focus on infrastructure challenges in Nigerian agriculture

Dawn et al. (2023)	AI-powered predictive analytics	Discusses real-time crop health monitoring and predictive analytics	Faces barriers like high costs and lack of expertise
Mathur (2023)	Biosensors and drones for crop productivity	Highlights AI's role in improving productivity and environmental sustainability	Barriers to implementation include technical skills and data privacy concerns
Rani (2021); Ravisha and Sinha (2023)	Machine learning for precision agriculture	Integrates field data, weather, and soil conditions to optimize crop selection	Does not specifically address Nigerian agricultural contexts
Eli-Chukwu (2019)	Automated agricultural tasks	Reduces water usage and increases productivity	High costs and limited digital literacy among Nigerian farmers

In Nigeria, recent studies have looked into how precision farming and machine learning might increase agricultural profitability and productivity. In their study "An Overview of Machine and Deep Learning Technologies Application in Agriculture: Opportunities and Challenges in Nigeria," Umar et al. (2022) emphasized the extensive use of machine learning in agriculture and focused on how it could increase food sufficiency in Kenya. The feasibility of implementing precision agriculture techniques in Nigerian maize plantations was demonstrated by Abdullahi and Sheriff (2017) in their work titled "Case Study to Investigate the Adoption of Precision Agriculture in Nigeria Using Simple Analysis to Determine Variability on a Maize Plantation." They did this by using fuzzy classification and simple image analysis to determine field variability and create treatment plans. In alignment, Abubakar et al., (2023) in their study titled "*Mapping maize cropland and land cover in semi-arid region in Northern Nigeria using machine learning and* Google *Earth Engine*" used machine learning free Sentinel-2 satellite imagery on Google earth engine to map maize croplands in Northern Nigeria. While the latter applied more advanced and scalable tools, both studies highlight the value of accessible, data-driven methods for improving site-specific decision-making in resource-limited farming systems. Although not specifically related to Nigeria, Rani (2021) presented pertinent smart-precision agriculture systems using machine learning algorithms in his work "A Deep Learner Based Smart Precision Agriculture System Using Machine Learning," and Ravisha and Sinha (2023) did the same in their study "Predictive Model for Smart Agriculture Using Machine Learning." To maximize crop selection and management, these systems combine weather factors, soil quality data, and real-time field information. Adoption of these technologies in Nigeria might greatly improve resource management, boost production, and improve agricultural decision-making, all of which would help Nigerian farmers overcome their issues. In their paper titled "Smart sensors and smart data for precision agriculture:" (2024), Soussi et al. analyzed integrated precision agricultural systems that combine smart sensors, IoT, and AI for automated, sustainable farm management, in line with the research of Rani (2021) and Ravisha and Sinha (2023). The latter emphasized larger system difficulties and scalability, providing insights that are extremely pertinent to the advancement of agriculture in Nigeria, whilst the former concentrated on particular applications. In the paper "Applications of Artificial Intelligence in Agriculture: A Review," Odirichukwu (2024). One study emphasizes the potential of AI technology in tackling important national development issues including insecurity, poverty, and corruption, while another highlights the influence of AI-driven IoT systems on air quality control (Engineering, Technology, and Applied Science Research). Farmers may monitor soil conditions, identify diseases, and boost agricultural output with the use of AI-powered devices like drones and biosensors (Mathur, 2023).

The potential of AI applications for sustainable development in Nigeria has been the subject of numerous researches. While Poronakie emphasizes the promise of AI technology in tackling important national development issues including instability, poverty, and corruption, Odirichukwu (2024) emphasized the influence of AI-driven IoT systems on air quality control. Future studies should take into account systems dynamics techniques, multidimensional perspectives, and psychological, sociological, and economic factors in order to optimize AI's potential for sustainability (Nishant et al., 2020). All things considered, AI has the potential to transform agriculture, making it more profitable, sustainable, and efficient while tackling the issues of global food security (Sharma et al., 2024).

Application of AI in sustainable Crop Production

AI application in crop breeding: The FAO (2017) found in their report "The state of food and agriculture: Leveraging food systems for inclusive rural transformation" that the agriculture industry is under tremendous pressure to increase crop yields and productivity in response to the world's population growth, which is expected to reach 10 billion people by 2050. There are now two ways to deal with the impending food shortages: increasing land use and introducing large-scale farming, or embracing new methods and utilizing technology to increase production on current farmland. Due to a number of issues impeding targeted farming production, including dwindling soil fertility, labor constraints, climate change, environmental concerns, and restricted land availability, the contemporary agricultural landscape is changing in a number of creative ways. AI-powered plant breeding has emerged as a key strategy for achieving food security and sustainable agriculture (Kundu, 2024). By simulating a large number of genetic combinations, breeders may precisely predict how these combinations would affect qualities like crop output, hardiness, nutritional value, and more. Using this predictive approach, scientists can purposefully breed the most promising combinations to produce crops that are nutrient-rich, disease-resistant, and high-yielding. AI technologies have the potential to support crop breeding in certain ways. Genomic selection: In their study, Khan et al. (2022) discovered that artificial intelligence (AI) is capable of analyzing vast amounts of genomic data in order to find genetic markers linked to desired characteristics, including yield, resistance to diseases, and nutritional content. By selecting plants with the best traits for future crop improvement, breeders can speed up the breeding process. The creation of DeepSea and DeepBind models represents recent developments in the evaluation and prediction of genetic traits.

Predictive modeling: AI is thought to be able to produce prediction models that simulate how different DNA combinations would appear in different settings. By allowing breeders to predict how different crop types would perform in different conditions without carrying out extensive field research, this saves time and money.

Faster breeding cycles: By speeding up the study of genetic data and forecasting the performance of various crop kinds, this AI helps breeders reduce the breeding cycle and quicken the release of new crop varieties. This skill aids in addressing new issues like the effects of climate change and changing pest and disease threats.

Weather forecasting and environmental protection: En-nagre et al. (2024) concluded that weather plays a significant role in agricultural planning and decision-making in their work titled "Assessment and prediction of meteorological drought using machine learning algorithms and climate data," and Hussain et al. (2018) concluded the same in their study titled "A dynamic neural network architecture with immunology inspired optimization for weather data forecasting." Several artificial intelligences are frequently used in weather forecasting. Based on patterns and trends, supervised machine learning techniques like random forest, support vector machine (SVM), and neural networks can be used to evaluate past data and predict future circumstances. Because Random Forest can handle high-dimensional data and non-linear correlations, it has been employed in weather forecasting (En-nagre et al., 2024: Hussain et al., 2018). Farmers may be able to obtain meteorological data through artificial intelligence technology, which would be useful for agronomic activities such as timely spraying, harvesting, and planting. By reducing crop dangers, this technology might increase crop production and revenues. Weather forecasts can also help with pest control, timely practice, and adopting preemptive actions to reduce input costs and yield loss. Price forecasting helps farmers make the most money by giving them a clear picture of crop prices in the upcoming weeks. Large data sets and intricate patterns can be analyzed by the AI algorithms to provide incredibly precise weather forecasts. Planning and proactive network management depend on this precision. By forecasting local weather patterns, the AI can help with resource allocation and make sure that resources are sent to the areas that need them the most (Mengistu et al., 2024).

Challenges and Limitations

Even though artificial intelligence (AI) has many advantages for agriculture, a number of obstacles and difficulties prevent its broad use, especially in developing nations like Nigeria. These difficulties include socioeconomic considerations, infrastructure constraints, governmental and regulatory issues, technical literacy and access, and other difficulties.

Technological Literacy and Access: In their study "Evaluating the impact of climate change on agricultural productivity in Nigeria," Ojo et al. (2021) found that a major obstacle to the adoption of AI in agriculture is farmers' lack of technological literacy. Due to their limited access to cutting-edge technologies, many Nigerian smallholder farmers may find it difficult to make good use of AI tools. Farmers may feel overwhelmed or unsure about how to incorporate AI into their current practices as a result of this knowledge gap, which frequently results in resistance to implementing new technology (Joubert & Jokonya, 2021). Additionally, access to AI technology is frequently restricted, especially in rural areas with low digital resources and internet connectivity (Khan et al., 2020). The potential advantages of AI cannot be completely realized without proper training and technology access, which puts many farmers at a disadvantage. This conclusion is supported by Zhang et al. (2019), who contended that the spread of AI in developing nations' agricultural systems is severely hampered by a persistent digital divide that is reflected in limited access to technology and digital skills. This suggests that a global obstacle to the use of AI in agriculture is access to and technology literacy.

Policy and Regulatory Challenges: In their paper "Artificial intelligence in agriculture: Applications and opportunities," Sullivan et al. (2020) found that the adoption of AI in agriculture may also be hampered by the lack of supportive legislation and regulatory frameworks. The integration of new technologies is frequently not sufficiently addressed by current agricultural policy, which causes uncertainty among investors and farmers. The development and application of AI solutions in agriculture may also be hampered by legal restrictions pertaining to data privacy, intellectual property rights, and technology transfer (Abiodun et al., 2018). To promote innovation and the use of AI technology in the agriculture industry, policymakers must set clear rules and support systems. In their paper "Governing artificial intelligence in agriculture: Challenges and policy directions for low- and middle-income countries," Sharma et al. (2024) affirmed this difficulty, arguing that the integration of AI in agriculture is severely hampered by the absence of strong legal protections and policy frameworks, especially in developing countries. This suggests that the implementation of AI technology for farming systems depends heavily on governance and policy.

Socioeconomic considerations: The adoption of AI in agriculture is significantly influenced by socioeconomic considerations. It is challenging for many Nigerian smallholder farmers to invest in new technology due to their tight budgets and other financial limitations (Ibitoye et al., 2021). Furthermore, these difficulties may be made worse by farmers' inability to obtain credit and financial services, which keeps them from using AI solutions that call for large upfront expenditures (Kudama et al., 2021). Furthermore, farmers' readiness to adopt AI may be influenced by cultural perspectives on innovation and technology. Some people may be resistant to implementing modern technologies because of firmly ingrained traditional farming methods (Zhang et al., 2019).

Promoting the effective integration of AI in agriculture requires addressing these socioeconomic obstacles. Klerlx et al. (2019) reinforce this finding by arguing that socioeconomic conditions, such as low financial resources, religion, and social exclusion, continue to be a major obstacle to AI adoption and smallholder farmers, especially in developing nations. Similar to the findings of Ibitoye et al. (2021) and Kudama et al. (2021), their research emphasizes that the majority of farmers will not be able to participate in digital transformation without specific financial tools like credit availability and subsidized inputs. They also point out that traditional farming methods and cultural beliefs fuel cognitive resistance to digital instruments. This suggests that removing socioeconomic barriers requires structural inclusion as well as technology availability. Adoption of AI sustainably depends not just on innovation but also on cost, a goal that needs to be reflected both domestically and internationally.

In conclusion, even if AI has the potential to revolutionize Nigerian agriculture, a number of obstacles and difficulties need to be removed in order to make its adoption easier. To enable farmers to effectively use AI technology, it is imperative to address socioeconomic issues, improve infrastructure, create supporting regulations, and increase technological awareness. By overcoming these obstacles, we can use AI to advance sustainable farming methods and increase food security. Farmers' lack of literacy, the high expense of AI equipment and upkeep, a lack of technological know-how, and data security and privacy are further problems.

Case Studies

Application of AI in Nigerian Agriculture: Empirical Evidence in Nigeria, the application of artificial intelligence (AI) to agriculture is becoming more widely acknowledged as a game-changing strategy for attaining sustainable farming methods. The impact of AI on Nigerian farming systems is demonstrated by actual data and case studies in this part, with an emphasis on increasing production, maximizing resource usage, and advancing sustainability. Sustainable agricultural change in Nigeria is being accelerated by the use of AI into contemporary farming methods. AI technologies are increasing productivity and supporting environmental sustainability through precision agriculture, insect control, and improved irrigation techniques. The case studies and actual data demonstrate how AI may be used to solve the problems facing Nigeria's agriculture industry, ultimately promoting both economic growth and food security. Nigeria's agricultural environment might be drastically altered by the broad adoption of these technologies as they develop further, promoting sustainability and resilience in the face of climate change and other difficulties. Nigeria is seeing a steady increase in the use of artificial intelligence (AI) in agriculture, which offers creative ways to boost output, improve resource management, and promote sustainable farming methods. This section provides more case studies and actual data demonstrating how AI is successfully changing farming systems throughout Nigeria.

Table 3: Empirical evidences of AI applications

S/N	Technique	Description	Source
1	Precision Agriculture	AI technologies such as remote sensing and machine learning are being used in Nigeria to implement precision agriculture. Farmers are using AI-powered drones for monitoring crop health, assess soil conditions, and enhance irrigation methods. These tools enable farmers to make data-driven decisions, resulting in higher yields and less waste of resources. For example, a study by Ojo et al. (2020) showed that farmers who used technology for precision agriculture had increased crop yields of up to 30% in contrast with conventional farming methods. This suggests that AI could increase agricultural productivity.	Ojo et al., (2020)
2	Pest and Disease Management	In Nigeria, AI applications for managing diseases and pests have produced encouraging outcomes. In order to examine crop photos and spot indications of insect infestations or illnesses, machine learning algorithms are being created. An AI-powered applications that lets farmers upload photos of their crops was developed as part of a study carried out by the International Institute of Tropical Agriculture (IITA). By analyzing the photos and offering suggestions for pest management techniques, the app greatly lessens the need for chemical pesticides and encourages more environmentally friendly agricultural methods. (IITA, 2021).	(IITA, 2021)
3	Market Access and Price Forecasting	Additionally, AI technologies are being used to increase farmers' access to markets. AI algorithms are used by platforms such as AgroDataTech to evaluate market patterns and give farmers updated information on crop demand and prices. This guarantees fair prices and lowers post-harvest losses by empowering farmers to make well-informed decisions about when to sell their food (AgroDataTech, 2021).	(AgroDataTech, 2021)

4	Irrigation Optimization	In Nigeria, AI tools are also used to improve irrigation techniques. In many places, smart irrigation systems that employ AI algorithms to evaluate weather information, soil moisture content, and crop water needs have been put into place. By assisting farmers in applying the appropriate amount of water at the appropriate time, these devices can reduce water use by up to 50% while preserving health of crops (Abioye et al., 2021). Thus, improves farming systems' resistance to climate fluctuation while simultaneously conserving water resources.	(Abioye et al., 2021)
5	Crop Yield Prediction	AI has played a key role in creating crop yield prediction models. In order to predict yields for different crops in Nigeria, scholars at the University of Ibadan used ML algorithms to examine soil data, historical weather flows, and performance of crop metrics. According to their research, farmers who applied these predictive models saw a 25% increase in production accuracy, which allowed for improved resource allocation and planning (Ogunniyi et al., 2022).	(Ogunniyi et al., 2022).

Future Perspectives

Looking ahead, AI will have a big influence on food sustainability and overall farming. Transforming from traditional tools to mechanized farming and artificial intelligence (AI), technology has steadily improved agriculture throughout history. Every invention has improved productivity and reduced difficulties in farming. The AI is capable of addressing the problems caused by environmental degradation, climate change, and the growing need for food. It has the ability to reshape modern agriculture by increasing yields, sustainability, and resource allocation. It also makes real-time monitoring possible, resulting in crops that are healthier and of higher quality. It is anticipated that AI would change farmers' jobs from manual workers to managing and overseeing sophisticated systems in agriculture. In the future farming community, knowledge of information technology solutions alongside agricultural business intelligence may be more valuable than the ability to use traditional tools or perform manual labor.

Innovation and Integration: To further improve agricultural methods, future research should concentrate on combining AI with high tech innovations like block-chain and the IoT. AI advancements like self-governing equipment and sophisticated analytics have the potential to overcome present constraints and increase the range of possible uses of AI in agriculture (Al-jalil et al., 2023).

Policy and Regulation: It is crucial to create laws and policies that encourage the moral application of AI while fostering innovation. Policymakers, tech companies, and agricultural stakeholders working together can successfully negotiate the difficulties and capitalize on the advantages of artificial intelligence in farming (Almzainy et al., 2023). In conclusion, the utilization of AI to farming systems is a noteworthy development that could boost sustainability, maximize resource use, and increase output. Even if there are obstacles to overcome, doing so and encouraging more innovation are crucial to achieving AI's full potential in improving agricultural operations.

5.0 Conclusion

AI has the capacity to revolutionize production of crop in both the ecological and economic domains. During this conversation, a number of important ideas were brought up, highlighting the substantial influence AI technologies can have on enhancing farming methods. The main finding is that farmers may make better judgments by using AI's capacity to optimize crop forecast through sophisticated data analysis. AI tools, like those used in precision farming, are essential for resource management. These instruments lessen the environmental effect of agriculture while simultaneously enhancing crop quality and yields by facilitating the accurate application of herbicides, fertilizer, and water.

This paper covers several AI tools that optimize agricultural processes, ranging from threshing to land preparation. AI-Driven technology has the potential to enhance environmental sustainability, economic growth, and food security despite adoption barriers, especially in poor nations. Expert system integration can improve decision-making and fill in additional knowledge gaps. All things considered, advancements powered by AI are critical to the future of sustainable agriculture.

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