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ENVIRONMENTAL AND ETHICAL NEGATIVE IMPLICATIONS OF AI IN AGRICULTURE AND PROPOSED MITIGATION MEASURES

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ABSTRACT

Numerous ethical and environmental questions are raised by the use of Artificial Intelligence (AI) in agriculture or precision farming. This study examines strategies that can solve environmental and ethical concerns as well as the negative effects artificial intelligence in agriculture may have on the environment and society. It employed a thorough literature study to determine the adverse effects of AI on the environment and ethics in Africa, as well as the suggested counter measures. The rate of carbon emissions is rising as a result of AI models, and constant power supply in our farms. Additionally, the ethical issues around data ownership rights, privacy and security, data bias, and the belief that AI in agriculture will someday entirely replace occupations designated for farmers were explored, along with suggestions for mitigating each of these issues. African academics, policymakers, and innovators are crucial for ensuring that AI solutions are in line with African priorities and requirements.

INTRODUCTION

Artificial Intelligence (AI) can be defined as the development of computer systems or applications that performs tasks that naturally should need human intelligence, such as problem-solving and decision-making (Russell & Norvig, 2016). AI systems are capable of analyzing and processing vast amount of data to gain knowledge and learn from experience. AI is a potent weapon that, if applied carelessly, can entrench and perpetuate evils while also distorting justice and amplifying favorable tendencies. Questions like who will be affected, when, and how if AI technology is applied in agriculture throughout Africa need to be addressed. AI has the potential to boost human capacities and provide African farmers' access to new markets through improved global chains. Although Africa is still in the early stages of implementing AI technology (Arthur 2021). It is expected that indigenous inventions and solutions will be distinctive because they would address closely-focused and distinctive issues. A lot of artificial intelligence techniques are already used for agricultural activities, including precision agriculture to help with plant disease detection, the use of autonomous robots to harvest large quantities of crops, soil monitoring, animal disease diagnosis, and IoT devices which stand for Internet of Things, referring to the concept of connecting physical devices to the internet, with the aim of allowing them communicate, and be controlled or monitored remotely. Due to the high cost of using AI in smart information systems, there may be a digital divide. Because it may be abused by dishonest governments, rival businesses, or even market traders. Agricultural big data, which refers to complex, large set of data that cannot be processed by the traditional data processing tools, but needs a level of AI tools, to provide valuable insights (Manyika et al., 2011) is likewise exposed to privacy and security risks. Robots, devices, and sensors have the potential to injure, distress, and harm the environment and animal welfare (Ryan 2019).

We have seen that artificial intelligence (AI) is a potent instrument that can assist in better managing the adverse effects on the environment by limiting damages to ecosystems and preventing further harm. Massive volumes of data can be used by ML-based technologies to help governments and decision-makers evaluate options for mitigation more quickly and thoroughly. Coincidentally, Floridi et al. (2018) described challenges encountered when implementing AI in agriculture and also proposed five principles to govern AI, including beneficence, which will encourage and promote well-being, preserving dignity, and sustaining the planet, or "do only good," and justice, which will uphold the rights of all people. "Do no damage" is implied by non-maleficence. Autonomy: This suggests that people have the freedom to decide for themselves, Justice: pertains to the allocation of resources and the abolition of prejudice and deals with shared benefits and shared prosperity, Explicability: focuses on making it clear that it's important to comprehend and hold artificial intelligence decision-making mechanisms accountable.

Environmental Concerns of AI in Agriculture

While opening the path for ecologically friendly procedures, artificial intelligence (AI) plays a crucial role in encouraging sustainable agriculture. However, unchecked, AI has the potential to degrade the environment. Among AI's detrimental environmental effects in agriculture are the following:

a. Carbon Emission: Researchers at the University of Massachusetts Amherst examined a number of natural language processing (NLP) training models to calculate the estimated energy cost and cost of electricity needed to train them. The resulting figures showed that the carbon footprint of training an AI model was about 300,000kg of carbon dioxide emissions, which is very significant to the degradation of the environment over time (Dhar, 2020). More concerns were directed to the carbon emitted by the infrastructure deploying the AI solution. For instance, in training an artificial neural network to diagnose soil defects, the carbon emission is directly influenced by the hardware on which the training occurred, the location of the training server, the energy grid used, and the training duration. Because it is currently unclear how much energy is used to construct large-scale AI systems for agriculture, it is impossible to monitor the environment's carbon emissions. The development of an emission calculator by Lacoste et al. (2019) to estimate energy and the impact on the training of machine learning models is one example of the work that has been done to estimate energy use in the literature. The carbon released into the atmosphere while training huge AI models has been doubling every 3.4 months since 2012, according to an analysis done in 2018 by the OpenAI research lab (Dhar 2020). It is clear that the energy required to run AI and IoT technologies consumes a significant amount of energy, and the use of fossil fuels to power AI solutions and advanced robots pollutes the environment.

b. Constant Power: Due to the minimal battery requirements and consistent power

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requirements of IoT sensors and agricultural robots, there may be an increase in greenhouse gas emissions and other problems related to global warming (Patelli & Mandrioli, 2020). The energy consumption of the AI machine over its lifetime and its impact on the environment become substantial because these agricultural robots work for a long period of time each day.

c. Electronic-Waste: The non-renewable materials used to create artificial intelligence (AI) solutions for agriculture end up as e-waste, and when electronic components become outdated or malfunction, they are discarded carelessly into the environment and add to the rising amount of "technotrash," which is extremely hazardous to the environment (Strubell, et al., 2019).

d. Soil Compaction: After doing extensive investigation, Nordic experts released their results on the detrimental impacts of heavy farm tractor operation on crop-growing soil. Their research demonstrates that using heavy machinery can permanently harm the soil, which has a cascading effect that results in increased land pollution, erosion, nutrient and pesticide loss, and lower agricultural yields (The Research Council of Norway, 2011). Heavy machinery's detrimental effect is known as soil compaction, which occurs when the pore system and density of the soil are harmed over an extended period of time and frequently result in permanent ruin.

Ethical Concerns of AI in Agriculture

Failure to provide the appropriate regulatory supervision and insight for AI-based technology is likely to result in a lack of transparency, safety, and ethical norms as a result of the rapid development of AI (Vinuesa et al. 2020). The following are some ethical precepts that have an impact on how artificial intelligence is used in agriculture:

a. Use of data and insights (Data Ownership and Intellectual Property)

Producers' viewpoints must change if they think that by exchanging information (anonymously) with their neighbors, they would have access to larger data sets that will enable them to identify trends and make predictions. It is concerning when farm data is exposed to outside parties (Rosenheim & Gratton 2017). Farmers worry that their information might fall into the wrong hands and be used against them (Ferris 2017). According to Coble et al., some farmers worry that sharing their data may place them in a difficult situation in the future, particularly in Africa (2018). They are concerned about the manner in which their information will be gathered and provided to entities affiliated with the government and regulatory bodies (Sykuta 2016). In a number of situations, such as regulatory enforcement, the imposition of taxes, fines, and limits, their data may be used against them. Using their information by commodity traders on the stock market is another worry (Ferris 2017). The issue of "whether farmers should transmit control of farm data to third parties" is brought up in relation to data ownership (Coble et al. 2018). There is concern that farmers' information might be used to contact them once more with unwanted commodities (Ferris 2017). "Large agricultural corporations like Monsanto may convince farmers to buy certain seeds, sprays, and tools and are likely to profit from the costs of their service and higher seed sales" (Ksetri 2014). It appears to be unclear who owns the data itself, who controls how it is used and executed, and who obtains it from farms (Kosier 2017).

b. Privacy and Security

As technology advances, it becomes more capable of being applied both constructively and destructively. Despite the possibility of anonymizing personal information, some social groups may nevertheless be negatively impacted by big data in agriculture. Decisions can be made and implemented on a large scale by authorities and enterprises, which may not be acceptable to farmers. To put it simply, "being identified as a member of a group may make individuals most vulnerable, as a broad sweep is harder to avoid than individual targeting" (Taylor 2017).

This is crucial in regions where data privacy rules are less strict. In sub-Saharan Africa, for instance, just 8 of the 55 countries have legislation controlling data protection (Taylor 2017). In the agriculture industry, this information might be used maliciously by dishonest governments, competitor companies, or even market traders. Currently, there is relatively little regulation of agricultural data (Ferris 2017). According to some sources, big data in the agricultural sector is less likely to raise privacy and security concerns than big data in other sectors (Zhang et al. 2014). This is because providers of agricultural technology do not collect data that is obviously sensitive, such as data on minors, banking information, or medical records (Ferris 2017). Despite this, farmers continue to provide a lot of details about their businesses. Names, addresses, property types, income ranges, and appraisals are among the personally identifiable information that is retrieved for processing (Ferris 2017). They are all private details, some of which are very delicate, like income. The right to privacy of third parties may also be violated by the use of drones and other data retrieval technology (Schönfeld et al. 2018). Farmers must feel safe in the use, understanding, and interpretation of their data (Lokers et al., 2016). Given that each vendor's services and platforms vary, the nature of data security concerns likewise varies, making it difficult to generalize this (Sykuta 2016). Additionally, the security needs vary depending on the type of data. Protecting information concerning a farmer's sales and yields, for instance, may be of considerably greater importance than safeguarding data regarding the quantity of rainfall the farm got.

c. Bias (Accuracy of Data and Recommendations)

AI systems are created by people, and people are inherently prejudiced and judgmental. Of course, biased data will continue to be used to train a lot of AI systems. In order to create AI systems that we can trust and algorithms that are easy to grasp, it is essential to develop and train these systems using objective data. Data sets utilized for human decision-making can contain prejudice and false assumptions, which is a serious issue when it comes to the manufacturing of food. When an AI model is being developed, it has a tendency to learn from a desired pattern of data rather than the actual distribution of data. If there are biases in the data or if there were biased assumptions made during algorithm development, the generated AI model will be biased. Additionally, the AI model created from the collected data may be biased if they do not accurately reflect the context or situation. AI bias may affect applications in agriculture (Dara et al 2022).

Furthermore, it's likely that context-related factors contributed to data retrieval that was dishonest or inaccurate. Animals may interfere with or affect the radio signals that are used by technical equipment to communicate, for example, causing it to malfunction (O'Grady &

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O'Hare 2017). Despite the fact that sensors may be shielded from harm, factors that lead to inaccurate readings, like temperature extremes and humidity, are a concern (Tzounis et al. 2017). Potential interferences must be considered in order to decrease erroneous readings, misleading analytics, and misguided prescriptions. Another potential concern is problems with data interpretation brought on by geographical differences or quirks. It follows that it is obvious that contextual data analysis is necessary in order to arrive at impartial judgments (Taylor et al. 2014). If these differences are not taken into account, the prescriptive analysis may lead to lost resources and harm to the farmer's livelihood. Agricultural technology suppliers must also have confidence in the accuracy and integrity of the information provided by farmers in order to make wise recommendations (Lokers et al. 2016). Despite the fact that the accuracy of data and recommendations is not intrinsically unethical, providing farmers with wrong data or making inaccurate recommendations may cause missing harvests, sick livestock, lost earnings, and other negative repercussions on their business.

d. Access to Technology and Data

Two issues with AI in agriculture are access to technology and how development is encouraged. Because they are often fairly expensive to develop and use for smaller farms and enterprises, new creative tools are typically only accessible to large cooperatives. Second, despite the fact that many farmers think they possess the technological know-how to use the data, Sykuta (2016) found that the data is usually unavailable to them. The technical skills required to assess this data may not be available to farmers for free, making them dependent on manufacturers of agricultural technology (Schönfeld et al. 2018). The role of farmers may be diminished as a result of data analytics, along with a number other related freedom. The problem of the digital divide, particularly in Africa, has a significant impact on access to AI-enhanced technology. Unjust power distribution that results from access to and control over farm data and AI technologies is another unfair situation that may be created by the usage of AI systems in farming. The ability to manipulate AI systems and access data from several farms can be abused by technology and service providers to exert market control, share data with third parties, and subvert farmers' ownership rights to their own assets.

d. AI replacing the labor force

Another issue for ethical concern is the use of AI robotics and its potential to eliminate jobs. As farming technology has advanced over time, there has been a decline in the necessity for full-time personnel. Fears regarding the future of employment seem plausible given that there will be less demand for labor as a result of the usage of "intelligent" equipment for many farm tasks. This could lead to "technical unemployment" and decreased remuneration. This also raises issues with inequality and adverse social transformation. The tractor is one such example of how technology has changed agriculture. In the United States, tractors gradually displaced horses and laborers between 1910 and 1960, according to Olmstead et al. (2001). In 1910, there were somewhat fewer than 12 million farm laborers. By 1960, this figure had dropped to 6 million. Additionally, society is growing more and more urban. People from rural areas are moving to cities, and many are no longer willing to put in the rigorous work required for farming. Due to the subsequent calamity in the business, farmers all over the world are turning to AI robotics to fill the hole.

Mitigation of Negative Impacts of AI in Agriculture on the Environment

a. Use of Automated Machine Learning Tools: Some strategies, such as utilizing a computationally efficient machine learning algorithm and resource-constrained devices, have been suggested to reduce the amount of carbon that is being released into the environment as a result of training and implementing AI systems. Software developers should refrain from creating new models from scratch because doing so will result in a considerable reduction in the carbon footprint and the amount of electricity required. To reduce carbon footprint, pre-trained models for search, speech, voice, and language projects are available from companies like Azure that provide cloud computing services. The in-laboratory activity should be discouraged in favor of automated machine learning. To promote cleaner AI practice and lessen environmental impacts in Africa, environmental standards should be developed and Green AI certifications should be launched.

b. Proper Recycling of Electronic-Waste: Recycling has proven to be the most effective method for preventing harm to our environment and health from e-waste. An organization called Great Lakes Electronics Corporation, which manages and recycles waste electronics, is based in Michigan. Also participates in sensitization about the importance of recycling and upcycling e-waste which will also help to reduce the risks brought on by this trash. In order to be utilized for longer and reduce the frequency of their disposal into the environment, the lifespan of AI equipment for agriculture needs to be extended as much as feasible.

c. Constant Power: An alternative energy source, laser fusion power, was proposed by the National Ignition Facility at the Lawrence Livermore National Laboratory in California. Laser fusion power produced more than 10 quadrillion watts of fusion power, outpacing its own energy consumption in a sustained synthesized reaction. The breakthrough was put on hold, nevertheless, when other facilities were unable to duplicate the experiment.

d. Deploy AI tools on lighter Machinery: Prevention is the best mitigation strategy for soil compaction. AI-enhanced tools should be deployed on lighter machineries.

Mitigation of Negative Impacts of AI in Agriculture on Ethics

a. Fairness: One of the ethical AI tenets, fairness, can be utilized to alleviate some of the ethical issues with using AI to agriculture. Fairness includes controlling and minimizing bias in the AI model, ensuring ethical data gathering and usage, and ensuring equitable access to digital assets (Jobin et al., 2019). All community members will profit from AI technologies in an equitable and inclusive manner with the right application of the fairness principle (Dara et al. 2022).

b. **Transparency and Interpretable AI models:** Individuals must be informed of the data acquired about them, whether they participated in decision-making, and the decisions that are made using their data in order for AI models to be transparent and interpretable. The level of human comprehension of the data's outcome. It's critical for the creation or administration of agricultural AI systems to be able to interpret data in order to increase transparency of AI technologies (Dara et al. 2022).

c. **Ensuring Data Privacy and Confidentiality:** The term "privacy" refers to the individual's ability to manage how their personally identifiable information is used,

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shared, and retained. Regulations and contractual obligations safeguard privacy. Contrarily, confidentiality is protected by agreements that are governed by law. Lack of control over personal data and questions about what information is gathered from farms, how it will be used, and who it might be shared with are the key privacy concerns. In order to protect data from cyberattacks, which are a legitimate issue, it is advised that businesses or persons that collect and use farmers' data have processes in place and publish them (Mishra 2022)

d. **Create Awareness:** AI has the capacity to boost agricultural productivity to previously unheard-of levels, which will be required to address the issue of food production. In order to prevent the possible gap between farmers and the AI technologies used on their farms from getting wider, the creators of AI models should involve farmers, especially during the data collection process. (Roadmap for research on ethical AI for development (AI4D) in African nations, Arthur Gwawa, 2021 agriculture as a case study). However, AI robotics do not work autonomously; they need human labor to operate and maintain them. Even if the skill set required for farming evolves throughout time, there will always be a requirement for some sort of labor on the farm. These technologies ought to be seen as an addition to human expertise rather than a replacement.

CONCLUSION

AI in agriculture has ethical and environmental issues that have come up or could come up as a result of its implementation, such as bias in the dataset used to develop some of these AI-based models, users' lack of confidence in the privacy and security of their data, lack of a reliable power supply, carbon emissions from various electronic devices that allow for the implementation of Artificial Intelligence and mitigation measures to solve problems, and lack of a constant power supply. Due to automation-related worries about data ownership and privacy, the use of algorithms in government procurement and distribution of agricultural inputs, and the requirement for agricultural and environmental justice to respect the rights of historically marginalized populations, it is crucial that the government prioritize ending the voting rights of African farm workers. This strategy can deal with the issue while keeping an eye on or mitigating any negative effects of AI in agriculture.

Depending on how much the technology affects inequality, we should be prepared to discuss legislation like antitrust laws and intellectual property rights frameworks that can promote sustainable and inclusive growth in agriculture. If the proper ethical and environmental standards are in place, the new technology can be used for the greater good and assist in creating a sustainable and abundant food ecosystem for years to come. artificial intelligence's contribution to the development of sustainability.

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