USE OF ARTIFICIAL INTELLIGENCE IN AGRICULTURE

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1 I INTRODUCTION

Agriculture is one of the main pillars sustaining humanity, being responsible for the production of food, fibers, and energy. However, due to population growth and climate change, the agricultural sector has faced significant challenges, such as the need to increase productivity sustainably, optimize the use of natural resources, and reduce environmental impacts (FAO, 2021). In this context, Artificial Intelligence (AI) emerges as a promising tool to revolutionize agricultural practices, offering innovative and comprehensive solutions that range from crop monitoring to process automation.

AI in agriculture, also referred to as precision agriculture, utilizes algorithms, sensors, drones, and data analysis systems to make more assertive and predictive decisions. According to Kamilaris and Prenafeta-Boldú (2018), the application of machine learning and computer vision techniques has enabled the early diagnosis of plant diseases, crop yield prediction, and efficient water resource management. These technologies not only increase productive efficiency but also contribute to cost reduction and the more sustainable use of agricultural inputs.

Beyond these applications, AI has also been employed in the development of autonomous systems, such as intelligent tractors and harvesters that operate with minimal human intervention (Zhang et al., 2020). These advances are particularly relevant given the current scenario of increasing rural labor shortages and the need for more precise agricultural practices with less dependence on external factors.

A review was conducted on the use of AI in agriculture, addressing its main applications, benefits, challenges, and future perspectives. The discussion is based on recent studies demonstrating the transformative potential of this technology, as well as the obstacles that still need to be overcome for its adoption on a larger scale.

2 I AI TECHNOLOGIES APPLIED TO AGRICULTURE

The application of Artificial Intelligence (AI) technologies in agriculture has revolutionized the sector, presenting a wide range of applications that enable process optimization, cost reduction, and productivity increase. Among the most important technologies are Machine Learning (ML), Deep Learning (DL), Computer Vision, Artificial Neural Networks (ANN), Natural Language Processing (NLP), and the integration between the Internet of Things (IoT) and Big Data.

Machine Learning and Deep Learning are widely used AI techniques for predictive analysis and decision-making in various fields, including agriculture. ML algorithms are employed to predict crop yields, identify climate patterns, and detect plant diseases based on historical and real-time data. For example, regression and classification models have been applied to estimate crop productivity based on variables such as soil type, weather conditions, and management practices (Liakos et al., 2018). Deep Learning, a subfield of ML, uses deep neural networks for more complex tasks, such as satellite and drone image analysis for crop monitoring. These techniques enable early detection of pests and diseases, as well as aiding in water resource management (Kamilaris & Prenafeta-Boldú, 2018).

Computer Vision has emerged as an essential tool for crop analysis through images captured by drones, satellites, and sensors. This technology enables the identification of anomalies such as water stress, nutrient deficiencies, and pest infestations with high precision. For example, drones equipped with multispectral cameras can capture detailed images of plantations, which are processed by computer vision algorithms to generate crop health maps (Zhang et al., 2020). This approach not only increases monitoring efficiency but also reduces the need for manual intervention.

Artificial Neural Networks (ANNs) are widely used in agricultural applications, particularly for weather forecasting and crop optimization. These systems can learn complex patterns from large volumes of data, such as historical temperature, humidity, and precipitation series, to predict future weather conditions. Additionally, ANNs have been applied to optimize the use of agricultural inputs, such as fertilizers and pesticides, based on the specific needs of each crop area (Pantazi et al., 2016). This personalization contributes to cost reduction and environmental impact mitigation.

Natural Language Processing (NLP) has gained ground in agriculture through virtual assistants and technical text analysis systems. NLP-based assistants can help farmers interpret climate data, receive planting recommendations, and find solutions to common field problems. Furthermore, NLP is used to analyze large volumes of text, such as scientific articles and technical reports, extracting relevant information for decision-making (Wolfert et al., 2017). This technology facilitates access to knowledge and promotes the adoption of more efficient agricultural practices.

The integration between IoT and Big Data has revolutionized agricultural data collection and analysis. IoT sensors installed in fields collect real-time information on soil moisture, temperature, light intensity, and other parameters, which are stored and processed on Big Data platforms. These data are analyzed by AI algorithms to generate insights that assist in crop management. For example, IoT and Big Data-based systems can predict irrigation needs or disease occurrences, allowing precise and timely interventions (Tzounis et al., 2017). This approach promotes precision agriculture, maximizing productivity and minimizing resource waste.

3 | PRACTICAL APPLICATIONS OF AI IN AGRICULTURE

Artificial Intelligence (AI) has been applied in various areas of agriculture, providing innovative solutions that enhance efficiency, reduce costs, and promote sustainability. These practical applications range from crop monitoring to process automation and intelligent management of natural resources.

Crop monitoring and management have significantly benefited from AI, especially through techniques such as remote sensing, satellite image analysis, and the use of drones. Sensors and cameras attached to drones or satellites capture multispectral and hyperspectral images, which are processed by AI algorithms to assess plant health, identify water stress, and detect pests or diseases at early stages (Zhang et al., 2020). This approach enables precise and timely interventions, reducing losses and increasing productivity.

Moreover, AI is used for early disease detection in crops. Machine learning algorithms are trained to recognize patterns in images that indicate the presence of pathogens, such as fungi or bacteria. For example, Deep Learning-based systems have been employed to identify plant leaf diseases with high accuracy, helping farmers take preventive measures (Mohanty et al., 2016).

Precision agriculture is one of the most promising AI applications, focusing on optimizing the use of agricultural inputs such as fertilizers and pesticides. AI systems analyze data collected by soil sensors, drones, and satellites to recommend the ideal amount of inputs to be applied in each field area. This personalized approach reduces waste, lowers production costs, and minimizes environmental impacts (Liakos et al., 2018).

Additionally, AI is used in recommendation systems for personalized management, providing specific guidelines for each crop type and soil condition. These systems integrate historical, climatic, and sensor data to suggest management practices that maximize productivity and sustainability (Wolfert et al., 2017).

Automation and robotics have been transforming agriculture, particularly with the use of autonomous tractors and agricultural robots. Tractors equipped with AI and GPS systems can perform operations such as planting, spraying, and harvesting with minimal human intervention, increasing efficiency and reducing errors (Zhang et al., 2020). Agricultural robots, in turn, are used for specific tasks such as harvesting fruits and vegetables, where precision and delicacy are essential.

Another relevant application is automated harvesting, which employs computer vision and AI algorithms to identify and harvest crops at the optimal time. These systems are particularly useful for high-value crops such as fruits and vegetables, where manual harvesting is costly and labor-intensive (Bac et al., 2017).

AI has also been widely used for climate modeling and crop yield forecasting, helping farmers make informed decisions based on future projections. Machine learning algorithms analyze large volumes of climate data, such as temperature, humidity, and precipitation, to predict weather conditions and their impacts on crops (Pantazi et al., 2016). These forecasts are essential for planning planting, irrigation, and harvesting.

Furthermore, AI-based predictive models are employed to anticipate the effects of climate change on agriculture. These models help identify vulnerable regions and develop adaptation strategies, such as selecting crops that are more resistant to extreme conditions (Lary et al., 2016).

Efficient management of natural resources is a key pillar of sustainable agriculture, and AI has played a crucial role in this area. Smart irrigation systems use soil moisture sensors and AI algorithms to determine the optimal amount of water to be applied in each field area, reducing waste and ensuring efficient use of water resources (Tzounis et al., 2017).

Moreover, AI is used for soil monitoring, evaluating parameters such as fertility, texture, and moisture. These data are processed by algorithms that generate recommendations for soil correction and fertilizer application, promoting crop health and environmental sustainability (Liakos et al., 2018).

4 I BENEFITS AND IMPACTS OF AI IN AGRICULTURE

The adoption of Artificial Intelligence (AI) technologies in agriculture has brought significant benefits, transforming traditional practices and promoting a more efficient, sustainable, and profitable sector. These benefits include increased productivity, reduced input waste, improved decision-making, and positive economic and agribusiness impacts.

One of the main benefits of AI in agriculture is the increase in productivity and operational efficiency. Technologies such as sensors, drones, and data analysis systems enable real-time monitoring of crop, soil, and climate conditions. This information is processed by AI algorithms to provide precise recommendations on crop management, such as the ideal timing for planting, irrigation, and harvesting (Liakos et al., 2018). As a result, farmers can maximize crop yields, reduce losses, and optimize resource use.

Additionally, the automation of agricultural tasks, such as harvesting and spraying, has increased operational efficiency. Autonomous tractors and agricultural robots equipped with AI systems perform these activities with greater precision and speed, reducing dependence on human labor and minimizing errors (Zhang et al., 2020).

Another relevant aspect is the humanization of agricultural work. By automating repetitive and physically demanding tasks such as manual harvesting or pesticide application, AI frees farmers to focus on less strenuous and more strategic activities, improving their quality of life.

AI has played a crucial role in reducing input waste, such as water, fertilizers, and pesticides, contributing to more sustainable agriculture. Smart irrigation systems, for example, use soil moisture sensors and AI algorithms to determine the exact amount of water needed for each area of the field, preventing excessive use of this resource (Tzounis et al., 2017).

Similarly, the application of fertilizers and pesticides is optimized through precision agriculture techniques. AI algorithms analyze soil and plant conditions to recommend the ideal dosage of these inputs, reducing costs and minimizing environmental impacts, such as soil and water contamination (Wolfert et al., 2017). These practices not only promote sustainability but also increase farmers' profitability.

AI has revolutionized decision-making in the agricultural sector by providing farmers with accurate and real-time information. AI-based systems integrate data from multiple sources, such as sensors, satellites, and weather forecasts, to generate insights that support crop planning and management. For instance, AI predictive models can anticipate pest or disease outbreaks, allowing for preventive interventions and reducing losses (Kamilaris & Prenafeta-Boldú, 2018).

Moreover, virtual assistants and AI-based data analysis platforms have facilitated farmers' access to technical knowledge and personalized recommendations. These tools help producers adopt more efficient and sustainable agricultural practices, even in regions with limited access to specialists and technological resources (Wolfert et al., 2017).

The adoption of AI in agriculture has had positive economic and agribusiness impacts, boosting the sector's competitiveness. By increasing productivity and reducing costs, AI technologies have contributed to improving farmers' profitability and expanding the agricultural market. According to estimates, precision agriculture powered by AI could increase global productivity by up to 70% by 2050, meeting the growing demand for food (FAO, 2021).

Additionally, AI has created new business opportunities, such as the development of agricultural data analysis platforms and AI-based consulting services. These innovations have attracted investments and fostered the creation of technological ecosystems in the agricultural sector, driving global economic growth (Wolfert et al., 2017).

Finally, AI has contributed to the economic sustainability of agribusiness by reducing dependence on expensive inputs and mitigating risks associated with climatic and market factors. Farmers who adopt AI technologies are better prepared to face challenges such as climate change and resource scarcity, ensuring the long-term viability of their operations (Liakos et al., 2018).

5 I CHALLENGES AND LIMITATIONS OF AI IN AGRICULTURE

Despite its promising benefits, the adoption of Artificial Intelligence (AI) technologies in agriculture faces various challenges and limitations. These obstacles include economic, technical, ethical, and infrastructure-related issues that can hinder large-scale implementation, particularly in regions with lower technological development.

One of the main challenges for AI adoption in agriculture is the high implementation cost. Technologies such as sensors, drones, data analysis systems, and autonomous equipment require significant investments, which can be prohibitive for small and medium-sized farmers (Wolfert et al., 2017). Additionally, the cost of maintaining and updating these technologies can also be high, limiting their accessibility.

In economically underdeveloped regions, access to these technologies is even more restricted, creating a technological divide among farmers of different scales and locations. This disparity can widen differences in productivity and competitiveness, exacerbating social and economic challenges in the agricultural sector (Liakos et al., 2018).

The effective implementation of AI solutions in agriculture depends on a robust infrastructure, particularly regarding rural connectivity. Many agricultural areas, especially in developing countries, lack access to high-speed internet and reliable communication networks, which are essential for the functioning of IoT (Internet of Things) and Big Data-based systems (Tzounis et al., 2017).

Without adequate connectivity, real-time data collection and transmission become unfeasible, limiting the effectiveness of AI technologies. Therefore, investments in telecommunications infrastructure are crucial to overcoming this challenge and ensuring widespread adoption of these solutions.

The complexity of AI technologies also presents a technical barrier for many farmers. The effective use of these tools requires specialized knowledge in fields such as data science, programming, and systems analysis, which are often beyond the reach of rural producers (Kamilaris & Prenafeta-Boldú, 2018).

Moreover, the lack of adequate training and capacity-building can limit the adoption and efficient use of these technologies. Education and rural extension programs are essential to familiarize farmers with new tools and ensure they can fully benefit from them. Without this support, there is a risk that AI technologies may be underutilized or misapplied, reducing their potential impact.

The adoption of AI in agriculture also raises ethical concerns and data privacy issues. The collection and analysis of large volumes of agricultural data, including information on farming practices, soil conditions, and climate, can lead to concerns about the misuse or commercialization of this data by third parties (Wolfert et al., 2017).

Additionally, the reliance on automated systems and AI algorithms can reduce farmers' control over their operations, raising questions about autonomy and accountability. For example, who is responsible for incorrect decisions made by AI systems? These issues require the establishment of ethical guidelines and clear regulations to ensure the responsible and transparent use of AI technologies in agriculture.

Despite these challenges, the future of AI in agriculture remains promising, with continuous advancements in technologies such as machine learning, computer vision, and IoT. The trend is for these tools to become more accessible and efficient, with lower costs and increased ease of use. Additionally, the integration of AI with other emerging technologies, such as blockchain and biotechnology, may open new opportunities for sustainable and intelligent agriculture (Liakos et al., 2018).

Another important perspective is the development of solutions tailored to the needs of small farmers and regions with limited infrastructure. Initiatives such as offline AI applications and low-cost systems can democratize access to these technologies, reducing the technological divide and promoting digital inclusion in the agricultural sector (Tzounis et al., 2017).

Looking ahead, the relationship between AI, science, and traditional agricultural practices has the potential not only to mitigate food and environmental crises but also to pave the way for a more resilient and human-centered agri-food system.

Finally, collaboration among public authorities, private entities, and research institutions is essential to overcoming current challenges and ensuring that AI's benefits are widely shared and democratized. These technologies should be accessible to all stakeholders in the agricultural sector, from small family farmers to large-scale producers. Investments in education, public policies, and infrastructure can accelerate the adoption of these technologies, making agriculture increasingly productive, sustainable, and resilient.

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