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Examining the Applications of Artificial Intelligence in Agriculture

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Abstract— In contemporary times, there has been a discernible incorporation of Artificial Intelligence (AI) applications inside the agricultural sector. The driving force behind this development stems from the enduring challenges faced by the agricultural sector. These challenges encompass concerns such as inadequate soil treatment, the prevalence of diseases and pests, the need for comprehensive data analysis, suboptimal agricultural productivity, and the disparity in understanding between conventional farming methods and advanced technology. The fundamental proposition underlying the involvement of artificial intelligence (AI) in the agricultural sector is based on its exceptional adaptability, superior performance capacities, precision in decision-making, and cost-efficiency. This study offers a comprehensive examination of artificial intelligence (AI) implementations in several domains of agriculture, encompassing soil management, crop management, weed control, and disease management. Significantly, the aforementioned statement underscores the importance of acknowledging both the positive attributes and constraints inherent in these artificial intelligence (AI) applications, thereby illuminating their capacity to bring about transformative changes in agricultural methodologies. Moreover, this research explores the application of expert systems in the agricultural domain, revealing its potential to bridge the knowledge deficit and enhance production in the farming sector. The potential for sustained growth and increased production in the agriculture industry is promising through the combination of AI's adaptability and the knowledge amplification of expert systems.

Keywords-Artificial Intelligence, Agriculture, Soil Management, Crop Management, Disease Management, Weed Management, Yield.

I. INTRODUCTION

The role of agriculture as a fundamental component of sustainability in any economy has been highlighted in previous studies [1]. The importance of food goes beyond basic nutrition, making a considerable contribution to long-term economic growth and supporting structural transformation, although there are variances across different nations [2-5]. Historically, agricultural practises were primarily focused on the production of food and crops [6]. However, in recent years, there has been a significant transformation in the agricultural environment. Currently, the field of agriculture comprises several activities such as processing, production, marketing, and distribution of both crops and livestock products. The multifaceted agricultural initiatives have emerged as a fundamental aspect of people's means of subsistence, contributing to the growth of the Gross Domestic Product (GDP) [7]. Moreover, they have played a significant role in enhancing national commerce, reducing unemployment rates, providing essential resources for diverse industries, and promoting overall economic progress [8-10].

Given the rapid growth of the world population, it is crucial to conduct a comprehensive evaluation of agricultural practises, with the aim of identifying novel strategies to support and improve agricultural activities. The incorporation of Artificial Intelligence (AI) in the agricultural sector is anticipated to be facilitated by a range of technological progressions, encompassing big data analytics, robotics, the Internet of Things (IoT), the widespread availability of cost-effective sensors and cameras, drone technology, and extensive internet connectivity across geographically dispersed agricultural areas. By utilising these techniques, artificial intelligence (AI) systems have the capability to analyse a wide range of data sources related to soil management. These sources include temperature, weather patterns, soil composition, moisture levels, and historical crop performance. The utilisation of data-driven methodologies enables artificial intelligence (AI) to provide predictive insights, hence assisting in decision-making procedures such as the selection of suitable crops for a particular year and the identification of optimal dates for planting and harvesting in certain geographical areas. As a result, these improvements possess the capacity to not only augment agricultural productivity but also mitigate the excessive use of water, fertilisers, and pesticides.

The utilisation of artificial intelligence (AI) technology in the agricultural sector also has the potential to address the adverse effects on natural ecosystems and improve the safety of workers. Consequently, this phenomenon leads to the maintenance of consistent food prices and guarantees the ability of food supply to match the continuous growth of the world population. In conclusion, the integration of artificial intelligence (AI) into the agricultural sector presents a great opportunity to address the changing demands of food production, while simultaneously promoting sustainability and economic advancement.

II. CONSIDERATION OVERVIEW

Agriculture is a domain characterised by a multitude of options and uncertainties, wherein every season presents its distinct array of obstacles. The issues faced by farmers include the unpredictability of weather patterns, fluctuations in the prices of farming inputs, soil deterioration, the cultivation of non-viable crops, encroachment by weeds, infestations by pests, and the constantly changing climate. Given the prevailing uncertainties, farmers are compelled to navigate a multifaceted and intricate terrain. This study concentrates on soil, crop, disease, and weed management within the context of agriculture, acknowledging their crucial roles in agricultural output.

The significance of soil in agriculture cannot be overstated, since it plays a crucial role in providing the necessary nutrients for optimal crop development. Soil serves as the fundamental basis for agricultural, forestry, and fishery production systems, acting as a reservoir for essential resources like water, nutrients, and proteins that play a critical role in supporting the growth and development of crops.

Crop production plays a pivotal role in Nigeria's economy, serving as a fundamental source of nourishment, raw materials, and employment opportunities. In contemporary times, the domain of crop production encompasses various facets such as marketing, processing, distribution, and post-sales services. There is an increasing focus on crop production and primary industries, particularly in places characterised by low per capita income. Improving the yield and efficiency of crop production can make a substantial contribution to a country's overall economic advancement.

In the face of the endeavour to address the requirements of a swiftly growing populace, the presence of plant diseases is a significant obstacle since they reduce both the volume and calibre of agricultural output. The potential ramifications of post-harvest infections on agricultural productivity are severe, emphasising the critical need for efficient disease management strategies.

Weeds also pose a substantial threat in the field of agriculture, persistently hindering productivity. These organisms encroach into agricultural fields, overwhelm grazing lands, and may endanger domesticated animals. Weeds engage in intense competition with crops for vital resources, including water, nutrients, and sunlight, resulting in diminished agricultural yields and poor crop quality.

In summary, the complex and diverse characteristics of agriculture necessitate the use of inventive strategies, namely in the areas of soil, crop, disease, and weed control. The use of artificial intelligence (AI) in these particular areas possesses the capacity to fundamentally transform agricultural practises, augment productivity levels, and fortify food security, so effectively tackling the significant issues encountered by farmers on a global scale.

- **DISEASE MANAGEMENT**

The attainment of maximum agricultural production is heavily contingent upon the implementation of efficient disease control measures. The presence of diseases in both plant and animal populations significantly hinders efforts to increase production. Numerous factors contribute to the incubation and dissemination of these diseases, encompassing genetic susceptibility, soil composition, meteorological variables such as precipitation, aridity, wind patterns, temperature variations, and additional elements. Managing the effects of disease-contributing variables poses a significant problem, especially in the context of large-scale farming operations, due to their unpredictable character.

Table I provides a comprehensive overview of artificial intelligence (AI) applications in the field of illness management, based on a thorough analysis of available scholarly literature. In order to efficiently manage diseases and minimise agricultural losses, it is imperative for farmers to use integrated disease control and management models that comprise a combination of physical, chemical, and biological methods (39). Nevertheless, the implementation of these extensive tactics may prove to be a time-consuming and inefficient use of resources (40). This highlights the urgent requirement for the utilisation of artificial intelligence (AI) methods in the control and management of diseases.

Explanation blocks (EBs) provide a clear and comprehensive understanding of the logical structure employed by expert systems [42]. Within the realm of crop disease control, a pioneering methodology is implemented, which incorporates the utilisation of fuzzy logic for the purpose of rule promotion. This innovative technique greatly enhances the formation of intelligent inferences. In addition, the integration of a text-to-speech (TTS) converter improves user engagement through the provision of a text-to-audio interface, so rendering it particularly efficient for real-time interactions on the internet [45]. A system has been built that utilises a rule-based, forward-chaining inference engine to identify disorders and provide recommendations for treatment [46]. The utilisation of AI-driven solutions in agriculture holds great potential for improving disease control measures, leading to increased efficiency and proactive management. This, in turn, can contribute to higher crop yields and the adoption of sustainable agricultural practises.

- **WEED MANAGEMENT**

Weeds present an enduring and substantial menace to agricultural practitioners, constantly reducing anticipated financial gains and agricultural productivity [51]. According to reports, it has been established that the failure to effectively manage weed infestations can lead to a significant decrease of approximately 50% in agricultural yields, specifically for crops such as dried beans and maize [51]. The wheat crop encounters a reduction in production of around 48% as a result of competition from weeds, and this figure can escalate to as much as 60% [52, 53, 54]. Research conducted on soybean and sesame crops has demonstrated significant decreases in yield, ranging from 8% to an astonishing 75%, when exposed to weed interference [55, 56]. The variations in agricultural yield losses can be ascribed to the length of time that crops and weeds coexist [57, 58], as well as the heterogeneity in the geographical distribution of weeds [59].

In addition to their influence on agricultural productivity, weeds have both advantageous and detrimental consequences on ecosystems. In accordance with a paper published by the Weed Science Society of America (WSSA), it has been observed that weeds possess the potential to exacerbate flooding events during storms. Additionally, several weed species have demonstrated the ability to flourish in the wake of wildfires. Moreover, specific weeds have been identified as being poisonous properties, capable of inducing irreversible liver damage upon consumption. Weeds pose an additional hindrance to the growth of plants and crops as they engage in competition for vital resources, including water, nutrients, and sunlight. Certain types of weeds possess toxic properties and might potentially endanger public health by inducing allergic reactions and posing health hazards.

Table I presents a concise summary of the various applications of artificial intelligence in the field of weed management. Despite the implementation of extensive weed control tactics reliant on herbicides in the preceding decades, it is currently projected that the financial impact of weed-related crop losses in field crops within western Canada continues to surpass $500 million on an annual basis [60]. This highlights the urgent requirement for the development and implementation of more sophisticated and specialised methods for weed management [51].

One novel strategy entails the utilisation of unmanned aerial vehicles (UAVs) for the purpose of imagery analysis. The aforementioned system employs a process of image segmentation to partition images, performs calculations and conversions of vegetation indexes into binary representations, identifies crop rows, optimises parameters, and constructs classification models. The utilisation of a crop row detection method is of great significance in accurately differentiating between crops and weeds due to the spectral similarities observed between them [64].

In addition, the utilisation of digital image analysis obtained from unmanned aerial vehicles (UAVs) for online weed detection, in conjunction with computerised decision-making and GPS-guided patch spraying, offers a feasible approach to address weed management challenges in various crops such as sugar beetroot, maize, winter wheat, and winter barley [67]. Drones have been shown to possess the capability to navigate at controlled speeds, as exemplified in a specific case [68]. They are able to swiftly identify the positions of tomatoes and weeds, and effectively guide the spray controller to provide precise weed management. The utilisation of AI-driven methodologies exhibits significant potential in mitigating yield losses, mitigating environmental consequences, and enhancing weed management practises within the agricultural sector.

- **SOIL MANAGEMENT**

The use of efficient soil management techniques is a crucial aspect of agricultural practises, as it significantly influences both crop productivity and the preservation of valuable soil resources. A thorough comprehension of various soil types and conditions is necessary in order to maximise agricultural results. Soil management comprises a range of activities, methodologies, and interventions aimed at improving the overall functionality of soil. In the context of urban environments, where soils have the potential to contain contaminants, conventional methods of soil survey can be utilised to examine and address possible concerns [11].

The utilisation of compost and manure is an effective approach to enhance soil porosity and aggregation, which plays a crucial role in mitigating the formation of soil crust. The integration of organic materials has been found to have a substantial impact on the overall quality of soil, presenting a viable and environmentally-friendly method for enhancing soil conditions [12]. Soil-borne diseases provide significant risks in the cultivation of vegetables and edible crops, requiring the implementation of rigorous control measures through careful soil management practises [13].

The evaluation of the sensitivity of soil deterioration plays a crucial role in assessing the sustainability of land management practises. The statement recognises the inherent heterogeneity of soils in terms of their ability to endure and rebound from negative effects [14].

Table I presents a succinct overview of methodologies and strategies employed in the domain of AI-driven soil management. The utilisation of management-oriented modelling (MOM) has become more significant in the effort to reduce nitrate leaching. MOM employs a systematic methodology that involves the creation of feasible management options, evaluation through simulation, and selection based on predetermined criteria. The MOM system utilises strategic "hill-climbing" and tactical "best-first" search techniques in order to ascertain the most optimal solutions [15].

The advancement of the Soil Risk Characterization Decision Support System (SRC-DSS) relies on three key phases: knowledge collection, conceptual design, and system implementation. These steps use principles from the field of engineering to improve soil risk assessment and management [16].

Artificial Neural Networks (ANNs) are utilised for the purpose of forecasting soil texture features, including sand, clay, and silt content. This is achieved by the integration of information obtained from coarse-resolution soil maps and hydrographic parameters produced from digital elevation models (DEMs) [21].

In addition, the remote sensing devices integrated inside higher-order neural networks (HONNs) enable the dynamic monitoring and assessment of soil moisture levels. This technological advancement enhances our ability to comprehensively comprehend and effectively regulate soil conditions [22]. The AI-driven breakthroughs hold the potential to significantly transform soil management, presenting novel ways to enhance agricultural practises and foster sustainability.

- **CROP MANAGEMENT**

Crop management involves a range of essential tasks, beginning with the initiation of seed planting and continuing with the monitoring of crop growth, the harvesting process, and the subsequent storage and distribution of crops. The aforementioned operations jointly strive to augment the growth and productivity of agricultural commodities. An in-depth understanding of diverse crop categorizations, considering their distinct temporal and soil prerequisites, is crucial for maximising agricultural productivity.

Precision crop management (PCM) is an advanced agriculture management system designed specifically to cater to the distinct requirements of crops and soils, with the primary objective of maximising profitability while simultaneously upholding environmental sustainability. Nevertheless, PCM has encountered difficulties, mainly attributed to the lack of prompt and extensively disseminated data regarding crop and soil conditions [26].

Farmers sometimes encounter the necessity of implementing a range of crop management measures in order to address water deficiencies resulting from several variables, including soil characteristics, weather patterns, and restricted irrigation resources. The preferred technique frequently involves the implementation of flexible crop management systems, which are driven by decision rules. The time, intensity, and predictability of drought are significant factors that have a crucial impact on the selection of appropriate cropping choices [27].

A comprehensive comprehension of meteorological patterns is of great significance in the process of making informed decisions, ultimately exerting an influence on the productivity and standard of crops [28]. In the realm of agricultural systems, cutting-edge technologies such as PROLOGUE make use of several factors such as meteorological data, machinery capabilities, labour availability, and operational characteristics to assess and enhance the performance of farm systems. This encompasses the process of approximating crop production, gross revenue, and net profit at both the level of individual fields and the entirety of the farm [30].

Crop prediction approaches integrate a range of soil and atmospheric data in order to anticipate the most appropriate crops for a given area. These characteristics comprise several soil variables, including but not limited to type, pH, nutrient levels, temperature, humidity, and rainfall patterns (Reference 31).

State-of-the-art technology such as Demeter, a computer-controlled speed-rowing machine, incorporate video cameras and global positioning sensors to ensure accurate navigation and strategic planning of harvesting activities. Demeter effectively implements its strategy by systematically dividing crop rows, readjusting its position within the field, and identifying unanticipated barriers, hence enhancing the efficiency of harvesting operations [32].

The utilisation of artificial intelligence (AI) in the process of cucumber harvesting encompasses a variety of hardware and software elements. These include self-driving vehicles, manipulators, end-effectors, computer vision systems for identifying fruits and assessing environmental conditions, as well as advanced control mechanisms to ensure the safe and efficient movement of manipulators during the harvesting process [33].

Moreover, AI-driven models, specifically Artificial Neural Networks (ANNs), employ field-specific rainfall data and weather variables in order to enhance the accuracy of rice yield projections. The adjustment of artificial neural network (ANN) parameters has a substantial impact on the accuracy of predictions. In the case of smaller datasets, it is observed that fewer hidden nodes and lower learning rates are necessary for achieving optimal model optimisation [38]. The utilisation of AI-driven breakthroughs has the potential to revolutionise crop management, enhance agricultural efficiency, and promote the sustainability of food production.

Table I Summary of Literature Review

Appl ioı	Authors and Technique	Strength	Limitation
AI IN SOIL MANAGEMENT	MOM (15)	Minimizes nitrate leaching, maximizes production.	Takes time. Limited only to nitrogen.
	Fuzzy Logic: SRC-DSS (16)	Can classify soil according to associated risks.	Needs big data. Only a few cases were studied.
	DSS (17)	Reduces erosion and sedimentary yield.	Requires big data for training.
	ANN (18, 19, 20 21)	Can predict soil enzyme activity Accurately predicts and classifies structure. Can predict monthly mean temperature It predicts soil texture and moist	Only measures a few soil enzymes. It considers more classification than improving the performance of the soil. Considers only temperature as a factor fo soil performance. Requires big data for training. Has restric in areas of implementation.
AI IN CROP MANAGEMENT	CALEX (29)	Can formulate scheduling guidel for crop management activities.	Takes time.
	PROLOG (30)	Removes less used farm tools fr the farm.	Location-specific.
	FUZZY Cognitive Map (35)	Predict cotton yield and improve crop for decision management.	It is relatively slow.
	ANN (36)	Can predict the response of crop soil moisture and salinity.	Considers only soil temperature and textu as factors.
	ANN and Fuzzy Logic (37)	Reduces insects that attack crops.	Shows inability to differentiate between c and weed.
AI IN DISEASE MANAGEMENT	Computer vision system (CVS)(42	Works at a high speed. Can mul task.	Dimension-based detection which may af good species.
	Fuzzy Logic (FL), Web GIS (43)	Cost effective, ecofriendly.	Inefficiency due to scattered distribution. Takes time to locate and disperse data. T location of the data is determined by a mo browser.
	Web-Based Intelligent Disease Diagnosis System (WIDDS) (44)	Good accuracy. Responds swift the nature of crop diseases.	Limited usage as it requires internet servi Its potency cannot be ascertained as only s crops were considered.

	FuzzyXpest provides pest information for farmers and supported by internet services. (48	High precision in forecast.	Internet dependent.
	Web-Based Expert System (49)	High performance.	Internet and web based.
AI IN WEED MANAGEME	ANN, GA (61)	High performance. Reduces trial and error.	Requires big data.
	Optimization using invasive weed optimization (IVO), ANN(62)	Cost effective, enhanced performance.	Adaptation challenge with new data.
	Mechanical Control of Weeds. ROBOTICS. Sensor machine learning (63)	Saves time and removes resistan weeds.	Expensive. Constant use of heavy machi will reduce soil productivity.
	Learning Vector Quantization (LV ANN (69)	High weed recognition rate with short processing time.	The method of data input used affected AI's performance.

Source: Various articles of review

III. CURTAILING CHALLENGES OF AI IN AGRICULTURE

Expert systems have the potential to serve as valuable instruments for agricultural management by providing location-specific, comprehensive, and interpreted guidance to improve farming techniques. Nevertheless, the development and extensive utilisation of these technologies in the field of commercial agriculture have been relatively new and constrained up until now (70). Despite some significant improvements, the impact of artificial intelligence (AI) on the agricultural industry still falls short of its full potential and is comparatively less influential than in other industries. There exists a compelling imperative to undertake further endeavours in order to effectively leverage the potential of artificial intelligence (AI) for the enhancement of agricultural practises, in light of the current constraints encountered during its deployment. Addressing the problems posed by artificial intelligence (AI) in the agricultural sector necessitates a collaborative endeavour including multiple stakeholders, such as researchers, farmers, policymakers, and technology developers. The following are essential techniques to effectively tackle these challenges:

In order to address the challenges posed by expensive data plans and inadequate internet connectivity in rural regions, it is imperative for governments and organisations to allocate resources towards enhancing internet infrastructure. This entails the provision of subsidies for data plans and the facilitation of affordable, AI-compatible gadgets to enhance accessibility for farmers.

• Education and Training: It is recommended to implement training programmes aimed at providing farmers with knowledge about artificial intelligence (AI) technologies and the advantages they offer. It is imperative for farmers to possess a high level of proficiency in utilising artificial intelligence (AI) technologies and systems in an efficient manner. It is imperative that these programmes are sustained in order to ensure that farmers remain informed about the most recent breakthroughs.

• Contextualised Solutions: Artificial intelligence (AI) solutions ought to be customised to cater to the distinct requirements and circumstances of several geographical areas and agricultural produce. Localised solutions have the capacity to effectively tackle distinctive difficulties, such as particular crop diseases or climate circumstances.

Collaboration among researchers, technology businesses, and farmers is vital in order to collectively develop and enhance artificial intelligence (AI) solutions. The contribution of farmers is of utmost importance in guaranteeing the practicality and efficacy of these technologies within real-world agricultural contexts.

The establishment of comprehensive legislation pertaining to data privacy and ownership rights in agricultural AI systems is imperative for governments. It is imperative that farmers retain authority over their data, ensuring that it is not subject to exploitation without their explicit consent.

• It is imperative for developers to give utmost importance to the interoperability of AI systems. Farmers frequently employ a diverse range of instruments and equipment in their agricultural practises, and it is imperative that artificial intelligence (AI) systems smoothly interface with these pre-existing technologies in order to optimise their effectiveness.

• The optimisation of resource utilisation, including water and fertilisers, is a crucial aspect to consider in the design of AI systems. This approach aims to minimise the environmental footprint of farming practises and enhance sustainability within the agricultural sector.

Continuous improvement is a crucial aspect in the field of artificial intelligence, whereby developers are encouraged to consistently update and refine AI algorithms with the aim of improving accuracy and performance. This entails using input from agricultural practitioners to enhance and modify the technology.

• It is recommended that resources be allocated by governments, agricultural organisations, and investors to provide assistance for research and development in the field of artificial intelligence (AI) as it pertains to agriculture. It is imperative to allocate funding towards pioneering initiatives that possess the capacity to address urgent agricultural issues.

• Facilitate the exchange of agricultural data and knowledge among farmers and researchers to promote information sharing. Open data projects have the potential to facilitate collaboration and expedite the advancement of efficacious artificial intelligence (AI) solutions.

A. The promptness and precision of response: A crucial characteristic of an intelligent or expert system is in its capacity to execute tasks with precision and efficiency within a limited time period. Numerous currently available systems have difficulties in achieving a satisfactory equilibrium between response time and accuracy, frequently exhibiting deficiencies in either one or both of these dimensions. The selection of a user's approach for task completion can be influenced by delays in system response. Typically, individuals select one of three strategies, namely automatic performance, pacing, and monitoring, by evaluating a cost function that considers the effort needed to synchronise the availability of the input system with the desired level of accuracy [71].

B. Requirements for Big Data: The efficacy of an intelligent agent is also dependent on the quantity of input data it is capable of processing. Efficient data filtering algorithms are important for real-time AI systems to effectively monitor extensive volumes of data on a continual basis. In order to provide prompt and effective response to crucial or unforeseen situations, it is imperative for the system to thoroughly analyse incoming data. This highlights the significance of obtaining comprehensive expertise on the work of the system from domain specialists and employing just pertinent data to improve efficiency and precision. The creation of agricultural expert systems is a multidisciplinary undertaking that necessitates the involvement of specialists from several agricultural fields and close interaction with the producers who will ultimately utilise these systems [70].

In summary, it is crucial to acknowledge and address the limitations associated with expert systems and AI in the context of agriculture, specifically pertaining to response time, accuracy, and big data management. By doing so, we can fully harness their transformative potential in optimising farming techniques and promoting the long-term viability of agricultural endeavours.

The efficacy of an expert system is heavily dependent on its technique of implementation. The establishment of a well defined methodology for data retrieval and training is of utmost importance in light of the increasing dependence on big data. This is necessary to guarantee optimal levels of both efficiency and precision. This involves the development of resilient algorithms and data structures that can effectively retrieve and manipulate extensive quantities of information necessary for decision-making.

One of the challenges associated with AI systems is the high cost of data. This issue is particularly prevalent in isolated or rural regions where internet connectivity may be restricted or expensive. Government initiatives can play a crucial role in providing assistance to farmers and facilitating the use of artificial intelligence (AI) systems in the agricultural sector. Governments possess the ability to provide web-based services and offer cost-effective device alternatives with decreased rates, specifically customised to smoothly integrate with artificial intelligence (AI) systems intended for agricultural practitioners. Moreover, the provision of training and retraining initiatives, such as comprehensive orientations on the utilisation of AI technologies, can enhance the capacity of farmers to embrace and efficiently employ these advanced tools within their agricultural operations.

One important aspect to consider is the concept of flexibility. The virtue of flexibility is of utmost importance in ensuring the robustness of an artificial intelligence system. Considerable advancements have been achieved in the use of artificial intelligence (AI) methodologies for individualised tasks. However, the current trajectory of AI-driven robotics technology is increasingly centred on the amalgamation of subsystems inside a cohesive and unified framework. This requires not only the flexibility of individual subsystems but also their ability to adapt and interact efficiently with other components. In order to expand its capabilities, it is imperative to develop an AI system that is adaptable and capable of incorporating more user data from field specialists. This would enable the system to integrate various expertise and insights. (Reference: [73])

In conclusion, it is crucial to address these factors, such as optimising the implementation approach, reducing the expenses associated with data acquisition, and improving adaptability, in order to fully harness the capabilities of artificial intelligence systems in the agricultural sector. The implementation of these processes is crucial in order to optimise the efficacy of AI technologies in driving agricultural progress, hence yielding substantial benefits for farmers and the agricultural sector at large. In summary, effectively tackling the obstacles associated with artificial intelligence (AI) in the agricultural sector necessitates a comprehensive strategy that spans various dimensions, including ensuring technological accessibility, promoting education, fostering collaboration, implementing regulatory measures, and demonstrating a steadfast dedication to sustainability. Through collaborative efforts and ongoing enhancements of artificial intelligence (AI) applications, we can effectively leverage the whole capabilities of AI to address the increasing requirements of worldwide food production, all while mitigating adverse environmental consequences.

VI. THE FUTURE OF AI IN AGRICULTURE

The predicted increase in the global population, expected to exceed nine billion by 2050, presents a significant challenge in terms of meeting the growing demand for food. It is estimated that agricultural production will need to expand by almost 70% to adequately address this pressing need. It is worth mentioning that the expanded production is anticipated to originate from previously unused lands by a mere 10%, underscoring the necessity for intensifying existing agricultural practises. In this particular setting, the incorporation of cutting-edge technical solutions into agricultural practises emerges as an indisputable must.

Contemporary approaches to enhancing agricultural productivity frequently depend on the utilisation of substantial amounts of energy, while there is a growing consumer preference for superior food items [74]. Robotics and Autonomous Systems (RAS) have the potential to bring about significant changes in multiple industries, including ones with comparatively lower productivity levels, such as the agro-food sector. This sector comprises the entire process of food production, starting from the farm and ending at the retail shelf.

The agricultural and food supply chain in the United Kingdom is a substantial driver of economic growth, with an annual contribution of more than £108 billion and a workforce of 3.7 million people. The industry, which operates on a global scale, holds significant importance in terms of exports, as evidenced by the documented export value of £20 billion in 2016 [75]. The integration of RAS technologies in the agricultural and food production industry has the potential to significantly transform the sector's efficiency, sustainability, and productivity. This adoption can play a crucial role in tackling the urgent issue of providing sustenance to an expanding global population while simultaneously mitigating environmental consequences.

REFERENCES

[1] M. A. Kekane, “Indian agriculture-status, importance and role in Indian economy”, International Journal of Agriculture and Food Science Technology, Vol. 4, No. 4, pp. 343-346, 2013

[2] B. F. Johnston, P. Kilby, Agriculture and Structural Transformation: Economic Strategies in Late-Developing Countries, Oxford University Press, 1975

[3] S. Kuznets, “Modern economic growth: Findings and reflections”, American Economic Association, Vol. 63, No. 3, pp. 247–258, 1973

[4] M. Syrquin, “Patterns on Structural Change”, in: Handbook of Development Economics, Vol. 1, Elsevier, 1988

[5] R. Dekle, G. Vandenbroucke, “A quantitative analysis of China’s structural transformation”, Journal of Economic Dynamics and Control, Vol. 36, No. 1, pp. 119-135, 2012

[6] M. Fan, J. Shen, L. Yuan, R. Jiang, X. Chen, W. J. Davies, F. Zhang, “Improving crop productivity and resource use efficiency to ensure food security and environmental quality in China”, Journal of Experimental Botany, Vol. 63, No. 1, pp. 13-24, 2012

[7] O. Oyakhilomen, R. G. Zibah, “Agricultural production and economic growth in Nigeria: Implication for rural

poverty alleviation", Quarterly Journal of International Agriculture, Vol. 53, No. 3, pp. 207-223, 2014

[8] T. O. Awokuse, "Does Agriculture Really Matter for Economic Growth in Developing Countries?", The American Agricultural Economics Association Annual Meeting, Milwaukee, Newark, USA, July 28, 2009

[9] O. Badiene, Sustaining and Accelerating Africa's Agricultural Growth Recovery in the Context of Changing Global Food Prices, IFPRI Policy Brief 9, 2008

[10] S. Block, C. Timmer, Agriculture and Economic Growth: Conceptual Issues and the Kenyan Experience, Harvard Institute for International Development, 1994

[11] C. R. D. Kimpe, J. L. Morel, "Urban soil management: A growing concern", Soil Science, Vol. 165, No. 1, pp. 31-40, 2000

[12] M. Pagliai, N. Vignozzi, S. Pellegrini, "Soil structure and the effect of management practices", Soil and Tillage Research, Vol. 79, No. 2, pp. 131-143, 2004

[13] G. S. Abawi, T. L. Widmer, "Impact of soil health management practices on soilborne pathogens, nematodes and root diseases of vegetable crops", Applied Soil Ecology, Vol. 15, No. 1, pp. 37-47, 2000

[14] J. K. Syers, Managing Soil for Long-Term Productivity, The Royal Society, 1997

[15] M. Li, R. Yost, "Management-oriented modelling: Optimizing nitrogen management with artificial intelligence", Agricultural Systems, Vol. 65,
No. 1, pp. 1-27, 2000

[16] E. M. Lopez, M. Garcia, M. Schuhmacher, J. L. Domingo, "A fuzzy expert system for soil characterization", Environment International, Vol. 34, No. 7, pp. 950-958, 2008

[17] H. Montas, C. A. Madramootoo, "A Decision Support System for Soil Conservation Planning", Computers and Electronics in Agriculture, Vol. 7, No. 3, pp. 187-202, 1992

[18] S. Tajik, S. Ayoubi, F. Nourbakhsh, "Prediction of soil enzymes activity by digital terrain analysis: Comparing artificial neural network and multiple linear regression models", Environmental Engineering Science,
Vol. 29, No. 8, pp. 798-806, 2012

[19] E. R. Levine, D. S. Kimes, V. G. Sigillito, "Classifying soil structure using neural networks", Ecological Modelling, Vol. 92, No. 1, pp. 101- 108, 1996

[20] M. Bilgili, "The use of artificial neural network for forecasting the monthly mean soil temperature in Adana, Turkey", Turkish Journal of Agriculture and Forestry, Vol. 35, No. 1, pp. 83-93, 2011

[21] Z. Zhao, T. L. Chow, H. W. Rees, Q. Yang, Z. Xing, F. R. Meng, "Predict soil texture distributions using an artificial neural network model", Computers and Electronics in Agriculture, Vol. 65, No. 1, pp. 36-48, 2009

[22] A. Elshorbagy, K. Parasuraman, "On the relevance of using artificial neural networks for estimating soil moisture content", Journal of Hydrology, Vol. 362, No. 1-2, pp. 1-18, 2008

[23] D. H. Chang, S. Islam, "Estimation of soil physical properties using remote sensing and artificial neural network", Remote Sensing of Enviroment, Vol. 74, No. 3, pp. 534-544, 2000

[24] T. Behrens, H. Forster, T. Scholten, U. Steinrucken, E. D. Spies, M. Goldschmitt, "Digital soil mapping using artificial neural networks", Journal of Plant Nutrition and Soil Science, Vol. 168, No. 1, pp. 21-33, 2005

[25] M. Kim, J. E. Gilley, "Artificial neural network estimation of soil erosion and nutrient concentrations in runoff from land application areas", Computers and Electronics in Agriculture, Vol. 64, No. 2, pp. 268-275, 2008

[26] M. S. Moran, Y. Inoue, E. M. Barnes, "Opportunities and limitations for image-based remote sensing in precision crop management", Remote Sensing of Enviroment, Vol. 61, No. 3, pp. 319-346, 1997

[27] P. Debaeke, A. Aboudrare, "Adaptation of crop management to water- limited environments", European Journal of Agronomy, Vol. 21, No. 4, pp. 433-446, 2004

[28] C. Aubry, F. Papy, A. Capillon, "Modelling decision-making processes for annual crop management", Agricultural Systems, Vol. 56, No. 1, pp. 45-65, 1998

[29] R. E. Plant, "An artificial intelligence based method for scheduling crop management actions", Agricultural Systems, Vol. 31, No. 1, pp. 127- 155, 1989

[30] H. Lal, J. W. Jones, R. M. Peart, W. D. Shoup, "FARMSYS-A whole- farm machinery management decision

support system", Agricultural Systems, Vol. 38, No. 3, pp. 257-273, 1992

[31] S. S. Snehal, S. V. Sandeep, "Agricultural crop yield prediction using artificial neural network approach", International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering, Vol. 2, No. 1, pp. 683-686, 2014

[32] T. Pilarski, M. Happold, H. Pangels, M. Ollis, K. Fitzpatrick, A. Stentz, The Demeter System for Automated Harvesting, Springer, 2002

[33] E. J. V. Henten, J. Hemming, B. A. J. V. Tuijl, J. G. Kornet, J. Meuleman, J. Bontsema, E. A. V. Os, An Autonomous Robot for Harvesting Cucumbers in Greenhouses, Springer, 2002

[34] H. Song, Y. He, "Crop Nutrition Diagnosis Expert System Based on Artificial Neural Networks", 3rd International Conference on Information Technology and Applications, Sydney, Australia, July 4–7, 2005

[35] E. I. Papageorgiou, A. T. Markinos, T. A. Gemtos, "Fuzzy cognitive map based approach for predicting crop production as a basis for decision support system in precision agriculture application", Applied Soft Computing, Vol. 11, No. 4, pp. 3643-3657, 2011

[36] X. Dai, Z. Huo, H. Wang, "Simulation of response of crop yield to soil moisture and salinity with artificial neural network", Field Crops Research, Vol. 121, No. 3, pp. 441-449, 2011

[37] C. C. Yang, S. O. Prasher, J. A. Landry, H. S. Ramaswamy, "Development of herbicide application map using artificial neural network and fuzzy logic", Agricultural Systems, Vol. 76, No. 2, pp. 561-574, 2003

[38] B. Ji, Y. Sun, S. Yang, J. Wan, "Artificial neural networks for rice yield prediction in mountainous regions", Journal of Agricultural Science, Vol. 145, No. 3, pp. 249-261, 2007

[39] BEA, Value Added by Industry as a Percentage of Gross Domestic Product, available at: https://apps.bea.gov/iTable/iTable.cfm?ReqID=51 &step=1#reqid=51&step=51&isuri=1&5114=a&5102=5, 2018

[40] Weed Science Society of America, Facts About Weeds, available at: http://wssa.net/wp-content/uploads/WSSA-Fact-SheetFinal.pdf

[41] J. Fang, C. Zhang, S. Wang, "Application of Genetic Algorithm (GA) Trained Artificial Neural Network to Identify Tomatoes with Physiological Diseases", International Conference on Computer and Computing Technologies in Agriculture, Wuyishan, China, August 18- 20, 2007

[42] K. Balleda, D. Satyanvesh, N. V. S. S. P. Sampath, K. T. N. Varma, P. K. Baruah, "Agpest: An Efficient Rule-Based Expert System to Prevent Pest Diseases of Rice & Wheat Crops", 8th International Conference on Intelligent Systems and Control, Coimbatore, India, January 10–11, 2014

[43] J. Jesus, T. Panagopoulos, A. Neves, "Fuzzy Logic and Geographic Information Systems for Pest Control in Olive Culture", 4th IASME/WSEAS International Conference on Energy, Environment, Ecosystems & Sustainable Development, Algarve, Portugal, June 11–13, 2008

[44] S. Kolhe, R. Kamal, H. S. Saini, G. K. Gupta, "A web-based intelligent disease-diagnosis system using a new fuzzy-logic based approach for drawing the interferences in crops", Computers and Electronics in Agriculture, Vol. 76, No. 1, pp. 16-27, 2011

[45] S. Kolhe, R. Kamal, H. S. Saini, G. K. Gupta, "An intelligent multimedia interface for fuzzy-logic based inference in crops", Expert Systems with Applications, Vol. 38, No. 12, pp. 14592-14601, 2011

[46] M. Y. Munirah, M. Rozlini, Y. M. Siti, "An Expert System Development: Its Application on Diagnosing Oyster Mushroom Diseases", 13th International Conference on Control, Automation and Systems, Gwangju, South Korea, October 20-23, 2013

[47] G. Liu, X. Yang, Y. Ge, Y. Miao, "An Artificial Neural Network–Based Expert System for Fruit Tree Disease and Insect Pest Diagnosis", International Conference on Networking, Sensing and Control, Lauderdale, USA, April 23–25, 2006

[48] F. Siraj, N. Arbaiy, "Integrated Pest Management System Using Fuzzy Expert System", Knowledge Management International Conference & Exhibition, Kuala Lumpur, Malaysia, June 6–8, 2006

[49] P. Virparia, "A Web Based Fuzzy Expert System for Insect Pest Management in Groundnut Crop 'Prajna'", Journal Of Pure & Applied Sciences, Vol. 15, pp. 36-41, 2007

[50] X. Wang, M. Zhang, J. Zhu, S. Geng, "Spectral prediction of phytophthora infestans infection on tomatoes using artificial neural network", International Journal of Remote Sensing, Vol. 29, No. 6, pp. 1693-1706, 2006

[51] K. N. Harker, "Survey of yield losses due to weeds in central Alberta", Canadian Journal of Plant Science, Vol. 81, No. 2, pp. 339–342, 2001

[52] M. Khan, N. Haq, "Wheat crop yield loss assessment due to weeds", National Agricultural Research Cen intensification tre, Vol. 18, No. 4, pp. 449–453, 2002

[53] S. Fahad, S. Hussain, B. S. Chauhan, S. Saud, C. Wu, S. Hassan, M. Tanveer, A. Jan, J. Huang, "Weed growth and crop yield loss in wheat as influenced by row spacing and weed emergence times", Crop Protection, Vol. 71, pp. 101–108, 2015

[54] A. N. Rao, S. P. Wani, J. K. Ladha, Weed Management Research in India-An Analysis of the Past and Outlook for Future, ICAR, 2014

[55] A. Datta, H. Ullah, N. Tursun, T. Pornprom, S. Z. Knezevic, B. S. Chauhan, "Managing weeds using crop competition in soybean [Glycinemax(L.) Merr.]", Crop Protection, Vol. 95, pp. 60–68, 2017

[56] T. Mruthul, Chemical weed management in sesame (Sesamum indicum L.), MSc Thesis, College of Agriculture, Raichur, University of Agricultural Sciences, 2015

[57] C. J. Swanton, R. Nkoa, R. E. Blackshaw, "Experimental methods for crop-weed competition studies", Weed Science Society of America, Vol.63, No. 1, pp. 2–11, 2015

[58] P. Jha, V. Kumar, R. K. Godara, B. S. Chauhan, "Weed management using crop competition in the United States: A Review", Crop Protection, Vol. 95, pp. 31–37, 2017

[59] P. Milberg, E. Hallgren, "Yield loss due to weeds in cereals and its large-scale variability in Sweden", Field Crops Research, Vol. 86, No. 2–3, pp. 199–209, 2004

[60] C. J. Swanton, K. N. Harker, R. L. Anderson, "Crop losses due to weedsin Canada", Weed Technology, Vol. 7, No. 2, pp. 537–542, 1993

[61] A. M. Tobal, S. A. Mokhtar, "Weeds identification using evolutionary artificial intelligence algorithm", Journal of Computer Science, Vol. 10, No. 8, pp. 1355-1361, 2014

[62] P. Moallem, N. Razmjooy, "A multi-layer perception neural network trained by invasive weed optimization for potato color image segmentation", Trends in Applied Sciences Research, Vol. 7, No. 6, pp. 445-455, 2012

[63] M. Brazeau, "Fighting Weeds: Can we Reduce, or Even Eliminate, Herbicides by Utilizing Robotics and AI", available at: https://geneticliteracyproject.org/2018/12/12/fighting-weeds-can-we-reduce-or-even-eliminate-herbicide-use-through-robotics-and-ai/, 2018

[64] M. P. Ortiz, P. A. Gutierrez, J. M. Pena, J. T. Sanchez, F. L. Granados, C. H. Martinez, "Machine Learning Paradigms for Weed Mapping Via Unmanned Aerial Vehicles", Symposium Series on Computational Intelligence, Athens, Greece, December 6–9, 2016

[65] L. Stigliani, C. Resina, "Seloma: Expert system for weed management in herbicide-intensive crops", Weed Technology, Vol. 7, No. 3, pp. 550- 559, 1993

[66] Y. Karimi, S. O. Prasher, R. M. Patel, S. H. Kim, "Application of support vector machine technology for weed and nitrogen stress detection in corn", Computers and Electronics in Agriculture, Vol. 51, No. 1-2, pp. 99-109, 2006

[67] R. Gerhards, S. Christensen, "Real-time weed detection, decision- making and patch-spraying in maize, sugarbeet, winter wheat and winterbarley", Wiley Online Library, Vol. 43, No. 6, pp. 385-392, 2003

[68] F. L. Granados, "Weed detection for site-specific weed management: Mapping and real-time approaches", Weed Research, Vol. 51, No. 1, pp.1-11, 2011

[69] C. C. Yang, S. O. Prasher, J. Laundry, H. S. Ramaswamy, "Development of neural networks for weed recognition in corn fields", American Society of Agricultural and Biological Engineers, Vol. 45, No. 3, pp. 859-864, 2002

[70] E. G. Rajotte, T. Bowser, J. W. Travis, R. M. Crassweller, W. Musser, D. Laughland, C. Sachs, "Implementation and Adoption of an Agricultural Expert System: The Penn State Apple Orchard Consultant",in: International Symposium on Computer Modelling in Fruit Research and Orchard

Management, ISHS, 1992

[71] S. L. Teal, A. I. Rudnicky, “A Performance Model of System Delay and User Strategy Selection”, Conference on Human Factors in Computing Systems, California, USA, May 3-7, 1992

[72] R. Washington, B. H. Roth, “Input Data Management in Real-Time AI System”, 11th International Joint Conference on Artificial Intelligence,
Michigan, USA, August 20-25, 1989

[73] P. Mowforth, I. Bratko, AI and Robotics: Flexibility and Integration,
Cambridge University Press, 1987

[74] D. G. Panpatte, Artificial Intelligence in Agriculture: An Emerging Era of Research, Anand Agricultural University, 2018

[75] T. Duckett, S. Pearson, S. Blackmore, B. Grieve, Agricultural Robotics: The Future of Robotic Agriculture, UK-RAS, 2018