

CASE STUDY



The impact of machine learning driven approach on agriculture and food industry: The case of a developing country

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ABSTRACT

The agriculture and food sector perform a fundamental function in human existence and also the economic well-being of any nation. This paper examines the concept of machine learning approach as it relates to the agriculture and food sector, its applications, also the impact on economic growth in developing countries. The 21st century era is faced with challenges like explosion in population, resource constraints, and climate change which are prevalent in developing countries. However, there are opportunities in this technological advancement era with heightened precision and innovation on the improvement of food safety, processing, quality for sustainability in the food ecosystem. Despite these advancements and opportunities there are barriers in the form of obtaining high scalable quality datasets, integrating multisensory inputs for food quality assessment, and meeting the demands for Graphics Processing Units (GPUs) for the optimization of deep learning models for food imaging. This paper is analyzing the application of machine learning in agriculture and food sector with a view to revolutionizing the traditional way of farming practices by leveraging on the technology for increased efficiency, environmental sustainability, better productivity in farming practices and improved food safety standards. We consider the integration of ethics in this study to address the concerns that has to do with privacy that associate with the collection and processing of data. Furthermore, stakeholders, scholars, practitioners, and policy makers can use it as a guide to increase research to navigate the ever-evolving technology-infused innovative agriculture that will shape the path to a robust, efficient and sustainable agri-food sector.

KEY WORDS

Machine Learning; Artificial Intelligence; Agriculture; Food processing; Efficiency; Sustainability; Developing Country

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Introduction

Agriculture accounts for the sustenance of people's lives and their economic well-being in both developed and developing countries of the world. This is seen in the general prosperity, which is dependent heavily on the annual harvest, as it links to food supply and distribution. Machine Learning (ML), which is a subset of artificial intelligence (AI), utilizes computational methods to improve system performance by learning from experience, underpinned by mathematics, statistics, and computer science [1]. The application of machine learning is making its impact on almost every field of endeavor and agriculture is inclusive. The agri-food industry's complexity is seen in the many wide ranges of challenges in the processes and operations, which in effect it is inefficient; so, the need for an innovative solution in the agri-food industry. This is to accommodate the many stakeholders found in trade unions and policy makers that also grows, produces, for an implementable sustainable solution. Employing technology as a tool in the digitalization of agriculture enhances the industry to become more efficient and sustainable. According to Mithun Ali et al., 2019; Rejeb et al., it makes up a key contributor to any nation's economy and is vital for the well-being of the nations' citizens [2,3]. Also, its importance in the developing and developed countries are seen in its role in the support of more sustainable production and consumption patterns, environmental protection, business competitiveness, social welfare, and economic growth [4].

In the contrary the machine learning is making its impact on almost every field agriculture inclusive.

Emerging economies characteristics are their varied stance on social and economic posture which put them on the threshold of taking control and advantage of all the possible opportunities AI offers and addressing both current and prevailing issues driving towards developing their economic base [5-7]. Therefore, adopting AI seems to advance some limitations that the conventional environment of the third world nations offers which call for a strategical guide to close the disparity existing potentially for effective implementation. So, the combination of ML with cutting-edge detection technologies will offer new opportunities to effectively address these challenges [8]. Therefore, automating agriculture has become important to transform the economy, as it creates a new course to explore [9]. Also, implementing machine learning successfully has revealed the identification of arable land for agriculture, high yield crop, and crop diseases. The implication from these is that sustainability in agriculture using ML in many of its applications have led to improvement in accuracy and efficiency of agricultural practices. This paper seeks to explore and contribute to the body of knowledge the technological and socio-economic nature of AI using machine learning (ML) in transforming their agri-food industry in developing countries for optimized farm yields and practices.

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Amir deduced in his work how agriculture has been transformed from old practices using artificial intelligence with machine learning. He highlighted the transformation in the following aspects; automation of decision processes that are complex, analyzing trends into the future, also integrating different sources of data. He goes further to emphasize on the need for continuous innovative stride to attain scalability, reliability, and complete automatic processes [10]. Iqbal et al., posit that technologies associated with AI do bring out a long-lasting, practical and best value found in food systems [11]. AI shows great positivity in the future of agriculture because of the inherent potential in rise in production that is sustainable and profitable even amidst difficulties [12,13].

A broad review of the literatures shows that artificial intelligence/machine learning has established auspicious results in high produce of agriculture and food sector. Studies also revealed that the use of machine learning algorithm modelling are effective in detecting soil type, crop diseases and abnormalities in crop yields. However, there is dearth of AI/ML policy framework by stakeholders and as rightly stated by Amir in his study that it is critical for stakeholders to be engaged and supported through policy frameworks to connect advancements in technology with societal and environmental values [10].

This paper presents the recent innovations of AI/ML

approaches in the agriculture and food sector and the many benefits it portends taking into cognizance the ethical considerations in a developing country. The study consolidates on inferences from recent articles published online, peer-review journals, review papers and proceedings of conference notably by analyzing the themes from interdisciplinary research directed at AI in transforming the food sector. The outline of the paper goes thus: it started by giving recent background/overview of agriculture and food processing and design using technology for sustainability. Afterward, it explores some AI models used in the transformation processes and steps both in the agriculture and food lifecycle. Accordingly, it studies emphatically the trends that may arise as a result of AI/ML deployment and barriers in the implementation. It further stated future trends and recommendations on the field of agriculture and food processing using AI and ML.

Theoretical Background

Several countries, the world over have initiated plans for the promotion of AI in all ramification of their life. This concept of artificial intelligence as defined by the European Union is a system with intelligent performance that analyze their environment and make out a fair result independently for a goal [14]. Figure 1 shows the makeup of AI and its interrelationship.

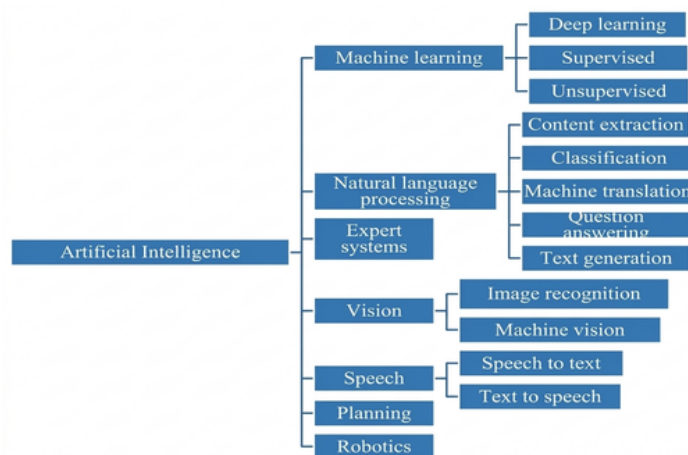


Figure 1. Branches of artificial intelligence [14].

The emergence of artificial intelligence powerfully shapes the world technologically, with its implementations in third world nations showing an extant changing description that transcend and influenced from several factors of recent, developing countries have increasingly accepted AI technologies because of their transformative power in catalyzing economic growth, enhancing public services, and addressing persistent societal challenges. They are driven by factors such as advances in technology, increasing connectivity, and the prevalent power of AI transformative abilities in real-time applications. This is seen in developing countries where governments and businesses leverage on AI to proffer solutions to issues that are complex in nature. For instance, from the work of AI is put to use in healthcare to enhance the investigative abilities and deliveries where there are few or no accessibility to healthcare

professionals. Also, the use of AI in agriculture for precision farming to optimize resource and improved yields. The education system is not left out too as AI is incorporated for improved personalizes learning.

According to Bačiulienė and Petroké the branches of AI relevant and mostly used in agriculture and food sector are machine learning, expert systems, computer vision and robotics [14].

Liakos, Busato, Moshou, Pearson, Bochtis, posit from their calculations that the emergence of machine learning with big data in agriculture goes together to produce new prospects that exposes, measures and realize the events taking place on the field from the data [15]. The various stages of Machine learning in the agriculture and food sector ss shown below in figure 2.

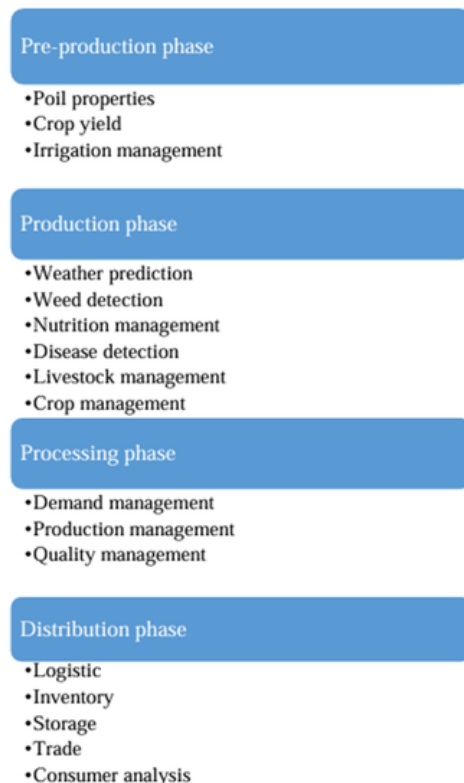


Figure 2. Stages of machine learning in agriculture-food sector [14].

Radocaj and Jurišić, developed a new study that forecasts how suitable cropland can be using GIS and ML. This is to promote and provide innovative standpoints for agricultural production resulting in improvement in decision making in agricultural management. Some notable countries which have contributed in researches of this nature is China who uses machine learning regression algorithms to obtain the leaf area index of cotton by means of spectral bands of Sentinel-2. This is a demonstration of the potency of this technology in the improvement agriculture. In addition, India's valuable contributions in the application of machine learning in crop production, can be seen from several examples ranging from crop prediction, and management for the purpose of productivity and sustainability. The review carried out by Liakos et al., on the use of machine learning in agriculture was popularly captured in the United Kingdom, which reflects the contribution to the scientific community and to consolidate knowledge and for future research. Also, studies conducted by Greece promotes and provides updates on the review of ML applications in agriculture, with the highlight on the various applications and their potential benefits [15-18].

The study carried out by the European Parliament's Committee on Agriculture and Rural Development gave a clear division of the applications of AI to three sub-divisions:

- Reduce risk involved in agriculture production such as new discovery of crop disease, the use of technology in the development of a concise soil maps for damage control);
- Reduce risk based on technologies and climate change.
- Increment in production efficiency such as controlling water and energy consumption.

- AI implementation in the agri-food industry comes in two categories:
- Digitalizing farm assets and activities, and
- Applying new methods in management.

Technologies that employ AI grows the throughput of many industries involved with it, and for the agric it is no exception. Farmers that employ technological solutions that is AI based tend to have better produce of high yields, at lower costs, with improved quality according to [19].

Methodology

The paper diagnosed recently published peer-reviewed articles based on AI and ML in the agriculture and food sector. The criteria emphasized appropriate technologies in high impact publications like journal papers, and proceedings from conferences.

The related works was searched using Google Scholar, Elsevier, IEEE, Springer and other links. This was realized with the help of keywords that captured the themes linked to the paper title. In the process of making use of Google Scholar, journal papers of high impact value and relevant to the topic a download was made. The search criteria also extended to papers that covers the integration of AI and ML with IoT, Blockchain, Deep Learning, written in English for clarity and easy access. It also considered papers whose methodologies can be replicated from the meaningful contributions of their outcomes that is impactful to life practically. It did not cover papers that are deficient in its techniques to replicate results and are bias thereby questioning the result.

Some AI models used in the agriculture and food sector

According to Bačiulienė and Petrokė the contribution of Artificial intelligence is significant in developing the food industry for automation, monitoring and control purposes of food quality. The use of machine learning methodologies has been employed by researchers and technicians to help in understanding the human behavior in deciding the food quality and food classification in accordance to the needs of the economy [14].

This is achieved from the following:

- The extraction of effective knowledge from humanly existing possible avenues.
- The establishment of guidelines to classify samples, without minding the complexity of the behavior of human and
- determining the extent of the impact i.e. relevance the result of the professional on the characteristic of the food [19].

There has been a surge in this contemporary era in ML applications, this is demonstrated in the steady growth of the user base as witnessed by ChatGPT from its commencement on November 20, 2022, which has generated questions ranging from ethical considerations, usability concerns, and the anticipated impact of ML and AI across various industries. Smart farming became relevant in 2021 because of the integration of cutting-edge technologies like unmanned aerial vehicle (UAV) in agriculture and internet of things (IoT) in food supply chain [20].

Sustainable agriculture uses ML to cause improvement in

accuracy to predict the nutritional guidelines for crops, which is important and beneficial when fertilizers are to be applied for plant health management [21].

Machine learning and Internet of Things (IoT)

In a similar situation, combining ML and IoT transforms smart agriculture and study recently acknowledge the use of these technologies in the automation of many agricultural tasks, like to monitor soil conditions, weather, irrigation management, and pest control. These applications bring about a reduction of farmers' workloads, improvement in farm practices and sustainability [22–26].

Machine learning and deep learning (DL)

Deep learning as used in agriculture sustainability creates models for prediction for identifying forms to make accurate classifications from huge datasets. This application is used to detect crop disease, species classification, and yield prediction, address complex agricultural problems and improve sustainable agricultural practices.

Machine learning and data mining (DM)

Data mining as used in ML in sustainable agriculture, extract forms and meaningful information from huge agricultural datasets. It analyzes old and current data that relates to the productivity of the crop, the soil type, and climatic variations, to facilitates and identify the trends for an informed decision making. This reveals concealed contributions for precise predictions significant enough for improved productivity in

agricultural practices.

Machine learning and convolutional neural network (CNN)

The convolutional neural network (CNN) utilizes machine learning tool to solve problems in smart farming. This is effective in the area of detecting and interpreting image complex patterns for tasks like classifying crop image, detecting diseases, and estimating yield due to their ability to extract information from the images. The advantage of this application is precision in managing crop efficiently, and improved sustainability of agriculture.

Machine learning and big data (BD)

Big Data voluminous data provides meaningful information for informed decisions. The concept of smart farming where large amounts of agricultural data is processed with that of climatic variations, crop yields, and management practices, results to better understanding of the patterns and trends affecting agricultural production. It helps to correlates and predicts future events in the area of improvement in data processing and storage techniques.

Machine learning and data analytics (DA)

Data analytics in ML extracts valuable meaningful inference from huge agricultural datasets. It identifies patterns and evaluates the different effective procedures ranging from managing the crop to using the resources. It results to optimized decision making, improved performance and reduction in the environmental impact.

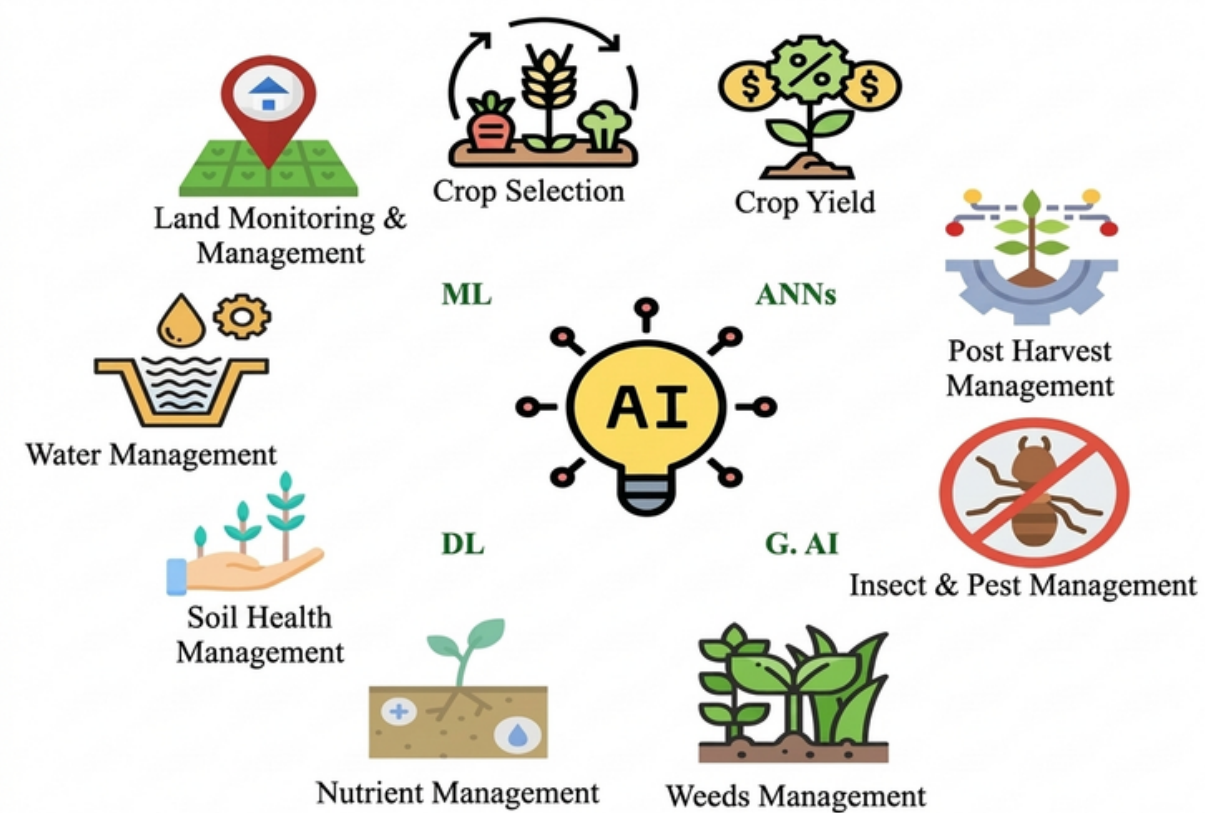


Figure 3. Applications of artificial intelligence [27].

Machine learning and computer vision (CV)

Computer vision helps in monitoring, developing, and predicting agricultural produce and the environment. This is aided by using sensors in fields and farms, for the collection of information for analysis. As a result, prediction can be made possible from the characteristics of the farmlands to check for drought, moisture, etc. Also, diagnosis of diseases affecting crops from the pictures of the foliage of good and unhealthy plants, and collection of other factors like temperature, sunlight, seeds, fertilizers, pesticides, and agricultural equipment. The investigation may result to detection of abnormalities not in agreement with certain standards that strengthens the worth of the produce. Also, computer vision checks the traceability of animals and their weight to guarantee healthy growth [14].

AI contributions in the food industry are classified mainly into three: management in terms of quality of the food, management in terms of security of the food, and management in terms of waste of the food as cited by Kovalenko [28].

Agriculture is the bedrock of most developing economies and AI and its related technologies will be significantly beneficial to it. Intelligent agriculture which is powered by AI, improves the use of resources, enhancing crop yields, and mitigating environmental impact. The applications of AI to monitor crops, control pest, and make predictions contribute

to sustainability in agricultural practices, which ensures food security and strengthens farmers livelihoods.

These applications highlight how integrating these cutting-edge ML concepts will improve policies, decision-making and enhance efficiency in the agricultural lifecycle.

- Land monitoring and management
- Agricultural water management
- Crop selection
- Soil management
- Crop nutrient management
- Weed control management
- Prediction of crop yield
- Pest and disease management
- Harvest and post-harvest management

Comparative Analysis of AI and ML in the Agriculture and Food Sector

The comparative analysis of ML algorithms should be the basis to evaluate and identify thoroughly and optimally models to predict problems that affects the different agriculture and food processing sector. Table 1 below shows the application of the models of ML and their effectiveness in agriculture:

Table 1. Comparison of ML models, applications and effectiveness.

ML models	Applications	Effectiveness	Author(s)
Performance metric between Machine learning (ML) and deep learning (DL) methods	Detection and identification of citrus plant leaf disease	The outcome from VGG-16 deep learning proved the best in accurate classification of diseases.	[29]
Integrating IoT and ML	Detect disease in crops ahead of time.	significant reduction in losses of crop, initial costs, and the overall management of the health of crop.	[30]
Adoption of IoT and ML	To measure the moisture of the soil also to establish the moisture levels and irrigation requirements	Regulates the properties of the soil simultaneously to prevent waste of water, increase in crop yields, which contribute to conserve resources.	[31]
SVM, & Decision trees	Classify detected contaminants	Detection of pesticide deposit, and bacterial infection.	[32-36]
Regression	Predictive Analysis	Prediction of the shelf life of consumables	[37-38]
Random forests, SVM	Quality control	Detection of flaws in food products	[39-41]
Logistic regression, SVM	Pathogen out prediction	Prediction of likelihood of outbreak from historical and environmental data	[42-45]

Economic Analysis

The initial high cost in the implementation of AI as envisaged by local practitioners may douse their enthusiasm to undertake these innovative technologies and as posit by Cervantes-Godoy is the issue of resistance to automate and mechanize local communities which they fear could lead to consequences of unemployment [46]. They also consider the high financial implications to maintain and upgrade and

according to Mukherjee the adoption of AI is broadly experienced in workplaces due to heightened automated jobs usually carried out by man; as a result, the local populace who rely on agriculture is affected [47].

Although, the implementation of AI can lead to the creation of new occupations in the agricultural ecosystem that will manage, operate and develop skills it calls for adequate training, tutoring and capacity training for its realization

which may necessitate the involvement of government in conjunction with organizations to make available subsidized incentives for easy access by farmers also, to boost jobs newly created in the ecosystem.

The survey of Agriculture Drone Market Size, Share, Industry Analysis, posit it that in the year 2019, the global farming marketplace value using drone was at USD one million with the expectation of reaching USD 3.7 million in the year 2027 while the use of robot with drone in agriculture is expected to get to USD 23 billion by 2028 [48]. The estimation given by Farrelly Mitchell, made it known that the global market value of blockchain in agri-food as at 2020, stood around USD 133 million; and it is projected to rise to about USD 950 million in the year 2025. Furthermore, the description according to the publication of Technavio, reported a 30% rise in production in the food sector which realizes the Government's plans [49]. Research by Kovalenko posit that there will be tremendous increase of \$9.28 billion by 2026 in the distribution network market of Big Data Analytics [28].

Case Studies

The successful integration of AI in agriculture has led to increased yields and several studies have shown for example, India uses AI to predict cultivation period excellent to grow crops on the basis of projections from the market and conditions of the weather which shows improvements in produce and proceeds of farmers [50,51].

Case study 1

The studies of Padhiary and Haydar et al. shows that John Deere, a world acclaimed manufacturer of agricultural equipment, integrates AI & ML in its smart farming. Its' tractors are self-driving with harvesters installed with devices able to detect and gather the actual information readily on conditions of the soil, health of crop, etc. This is achieved using the algorithms of machine learning to evaluate the data, for an informed decision on water management, and applications of fertilizer and pesticides. This innovation improves the growth of farmers produce with a reduction to cost and harm to the environment. This in-turn improves operations efficiently, supporting sustainability, in the practice of agriculture [52,53].

Case study 2

Maitra and Damle, cited in their work a mobile app called Plantix designed and implemented by PEAT an AgriTech startup company. It helps in the detection of diseases in crops using AI and image recognition from pictures initiated from farmers phones. The images are analyzed, diseases, pests and deficiencies in the nutrients are identified and it recommend treatment solutions [54].

The effect of this technology cultivators in India and emerging economies improve the growth of their produce which allows for advance discovery and remedy of diseases, to reduce cost and improve security of food.

Case study 3

Pham and Stack in their work explains how Climate Corporation, used AI to improve irrigation. It does it using the Climate Field View platform, and combining forecasts from weather, data from field and moisture from soil to recommend the irrigation position to farmers [55]. Birner, et al., sum it in

their work that it enables farmers using ML models to forecast water supplies on the basis of the existing situations for efficient use of water [56].

The implication of this is water conservation, reduction in energy usage and improve irrigation expenses, despite preserving the health of crop particularly in drought areas.

Case study 4

LeMieux and News, introduced Monsanto in the work and Kock explained the use of AI and the technology CRISPR gene editing in fast tracking crop breed. It analyses large genomic data and the algorithm separates desire qualities like water resistant, pest resistant and high yields that will enable genetic modification of the crops to withstand different climatic conditions and disease resistant [57,58].

This work has been able to develop a robust, genetic modified variations of crop yields in high proportions to meet the growing demand as well as secure food in our world.

Case study 5

Kirpach and Riccoboni in their study indicated the use of AI and computer vision designed by Cainthus, which is a startup company called agri-tech to track the actual behaviour of livestock. The use cameras that are installed in different position of the sheds while the AI algorithm evaluates the movement, health and feeding forms of the animals. The data obtained by the farmers is used for the improvement and well-being of the animal [59].

This Cainthus' smart AI farm for livestock has a high yield in the making of milk, reduction in cost of treatment, and the overall improvement in the health of the animals which leads to greater economic gains and sustainable farming in livestock.

Case study 6

Misra et al., in their work shows how Microsoft company uses its software Azure by engaging artificial intelligence and machine learning in tackling impediments to food security. It monitors the actual indices, predict time to maintain the system also analysis data. This improved operations of stakeholders in the food industry by securing, preserving the standard of their products [60].

Case study 7

According to Food Safety and Quality, their study conducted on Tetra Pak shows the integration of AI to process and package food to further fortify its value and security. The algorithms do it by monitoring, optimizing process environments, detection of irregularities, also, preserve the authenticity of produce packed integrity of packaged products from manufacture to the end user [61].

Implementations of ML in some Emerging Economies

The implementation of AI in some emerging economies can take the form of diverse initiatives to harness technology thereby addressing the precise tasks which boosts socio-economic development. The section below showcases the transformative power of AI implementation in agriculture in some selected developing countries.

Intelligent Agriculture

India leverages on AI in their agriculture which is the foundation of their economy for enhanced intelligent farm undertaking as

cited by Tiwari and Jaga, Rana. A company called CropIn uses AI in analyzing satellite images, data from weather and soil conditions. According to Shaktawat, and Swaymprava farmers do obtain custom-built instructions on the management of farm produce, and farmlands using their phones. This is an AI – ML driven approach for resource optimization, improvement of crop yields which characterizes sustainability in agriculture [62-64].

Pye-Smith in his work on how farmers utilize digital technologies in East Africa expressed his views that more than half of Africa's populace thrive on agriculture and the farmers are small holder farmers. Their work posited the transformation of poverty through agriculture but, that many of the farmers do not have the requisite know how and skills to transform the practices of farming [65].

Apraku, Morton and Apraku-Gyampoh posit that Kenya's economy is anchor on agriculture for its growth and expansion. Of note, climatic change and non-large-scale agriculture in Africa accounts for 24% of the Gross Domestic Product while above 70% of its workforce engage in rural farming [66].

Awuor, Kimeli, Rabah and Rambim in their study noted the significant role of agriculture particularly in rural communities of several developing countries. This is seen in the area of growth in agricultural productivity to sustain the requirements of the populace, decrease in soil fertility, water deficiencies and climatic change and so on. Although, challenges do exist employing Information Communication Technology (ICT) in agriculture potentially increase efficiency, productivity and sustainability through sharing of information and knowledge. The development of e-agriculture framework equips farmers with adequate information on pre-harvest, post-harvest, sales, and weather forecasts [67].

Ethics in Agriculture and Food Sector Management

The rise in the use of data in the agriculture and food sector has warranted close attention to ethics and privacy which concerns gathering, storing, and using vital data obtained from farming . It takes the form of non-disclosure of data, consensus, owning the data, and using the inference responsibly. The ethical consideration ensures impartial use of algorithms, preservation of individual information, also granting same approach to beneficiaries technologically which are vital to the development of AI for fairness, clearness and for the common good. This ensures that ethic and clear management of data are very important to build confidence amongst farmers, investors considering the protection of their sensitive information. This can be addressed by establishing a clear-cut approach that is transparent and secured. To the realization that these farmers are to be provided with succinct information on gathering procedures of the data, with clear information about the data collection processes, the method of use, how the data can be used, and the phases involved for confidentiality and safety [68-71].

Barriers Encounter in Implementing AI-ML

A barrier that is significant in implementing AI effectively is the lack of adequate infrastructure like unreliable internet connectivity, inadequate computer facilities, and storage resources for AI deployment. The deficit in infrastructure deters the seamless integration of AI technologies. ITU puts it that inadequate connectivity and power supply causes impediment in real-time AI application processing demands,

which creates a divide digitally across regions that have and those that do not have enough infrastructure.

Digital divide

The work of Treinen, Van der Elstraeten and Pedrick noted that rural dwellers are worst hit when it comes to the divide digitally and gender wise. This was captured in ITU, where statistics show the penetration of women using internet was 12% lower than that of men combined worldwide. But, in Africa, it is high as 25% lower when compared to men using the internet. This is seen in the complexity of systems using AI, and the necessity and reliability for a powerful data processing and internet connectivity respectively which are not common in local areas or areas not too close to urban centers [72,73].

Another barrier that may arise is the issue of cybersecurity and data privacy which would be as a result of reliance on platforms digitally to carryout agricultural operations such as storage and data processing using the cloud. Nevertheless, the solution in adopting AI can take the form of scalability, and ease of maintenance to operate effectively where technology is underdeveloped. Although, what is expected is cooperation by ensuring that those providing the technology, government, concerned stakeholders make the benefits of AI accessible to the farmer, regardless of location or financial status [74,75].

Culture and beliefs

Ryan noted in his work that the skepticism by several farmers to innovations and their continuous attachments to legacy cultivation approaches calls for their opposition. Also, there is the issue of farmers unwillingness to accept AI-driven solutions as a result of gap in generation in adopting technology, as pointed out by Belcher [76,77].

For instance, the opinion of Gill noted that ICT challenges or the related issues in the Indian agriculture has to do with variety in the spoken languages, culture and inadequate knowledge have been an obstacle in bringing rural Indians together for a common goal. The arguments put forward by Akokuwebe and Odularu indict women of being liable to societal factors like denial of education, inappropriate distribution of inheritance, and denial of power to take control of resources all these makes accessibility to loans and other funds difficult for them. This barrier can be overcome using instructional guides, and outreaches to show the advantages AI pose in the agricultural and food sector to cultivate hope and assurance in the use of the expertise. According to Maraveas, the change to AI-based technologies demands a slow but steady, stimulating and thought-provoking exercise practically and mentally [78-81].

Low literacy

Balraj and Pavalam in their work to explore the impact of ICT in agriculture in Rwanda, identified illiteracy among small holder farmers resulting to lack of the needed awareness to promote the technology so the adoption becomes unachievable. This can be overcome by focusing on the education of both the accomplished and the novice farmer on using AI. The curricular should include usual issues and difficulties in implementing it but identifying the immediate advantages in from of high produce and reduced workforce expenditure [81-83].

Infrastructural deficit

The issue of infrastructural deficit in developing nations can be tailored to the exorbitant nature of the equipment. The study of Dhaka and Chayal noted that the lack of infrastructure facilities

like power supply pose as hindrance to ICT take off in rural areas of India. The implementation of innovative technology like AI, IoT devices, and automation is usually costly [84].

It links to the devices itself, computer programs, skills development, and current up and running cost [85]. The cost of projects can be brought to a manageable level by organizations employing approaches in stages like having to start a test model. They can leverage services hosted on the cloud while requesting for grants or subsidies from government and industry respectively to ameliorate the original expenses. Having to collaborate with experts that provides the technical know-how also partnering with industry can bring about a reduction in cost by way of distribution and optimizing the resource.

Others

This includes lack of a robust dataset from the geographical location to fit the climatic conditions for adequate insights to solve localized problems. Also, the case of model being scalable, interoperable, interpretable, with the aid of images from satellite, radars, and forecasts from climatic data. Also, there is the case of farmers resisting the technology, as this requires tutelage, and disclosure and discussion of regulation and confidentiality. It is therefore important that there is a vibrant regulation on the use of AI putting into consideration issues of ethics and confidentiality of data that are not inimical to innovative processes. This can be achieved by bringing together all stakeholders in a town hall meeting to frame guidelines to show the advantages of AI over concerns socially and ethically.

Lack of trained workforce in AI - ML technologies

Developing countries face the challenge of struggling with lack of professionals who are trained in machine learning, data science, and AI development. To bridge this gap there is need to organized training programs to educate employees. World Bank made it clear on the need to build curricula for establishments that are into training to be AI inclined, to ensure that employees prepared adequately with the requisite and exquisite skills necessary to leverage on AI efficiently. Dhal and Kar pointed the need to partner with institutions of learning also with professionals to provide expert tutoring this can be valuable [86,87].

Risk Analysis and Mitigation Strategies

The implementation of ML techniques in agricultural processes also introduces confidentiality worries which stem from the continuous collection of sensitive information like, moisture of the soil, degree of hot/cold of the soil, health of crop, functional facts, liable as vulnerabilities on transmission through the cloud, mobile apps, and can be hacked, using accessibility not authorized, in addition misused [88]. According to Sonka, the consequence of exposing information of such magnitude lead to theft of intellectual property, otherwise shortcoming in the competition, especially when handled by competing things whose goal is to exploit the farmer for example, firms involved in technology, and information brokers [89]. The hazards are more at the grassroot centers, due to inadequate knowledge and governing of the area. The mitigation strategies to these hindrances are development of a strict encryption strategies for the transmission of data, anonymity to avoid re-identification, and stringent controls to accessibility of data not-authorized for

use. Also, to realize the complete capacity inherent in AI technology it is dependent both on the support of policy frameworks and functional stakeholders' participation [10]. These policies encourage growth, distribution, and the implementation of innovative data-driven farming appliances considering also hindrances as regards to confidentiality, training and capacity building, and unbiased transfer of technology.

Conclusion

In conclusion the use of emerging technologies like Artificial Intelligence and Machine Learning in the agriculture and food sector brings about automation which increases productivity. This aids in the collection, storage, and data analysis for increase in product quality and user-friendliness. A theoretical assessment of AI and ML for developing countries shows a huge worth in value that is added to agriculture, and the processing of food. There are improved labor productivities which is evident in the impact and transformation AI brings in reshaping the agriculture and food sector and their overall trajectory of development. These potentials are vast, and it has become eminent and appropriate for research and innovation to go into AL. Moreover, increase in farm investment which is the livelihood of developing countries makes it a precondition for the agriculture and food sector to thrive and increase these myriads of opportunities. AI/ML has proven to be a positive catalytic change agent.

Although, developing countries encounter some challenges in infrastructure, skills, digital divide, cultural beliefs, illiteracy, there are still opportunities to advance these age-long limitations. Policies and initiatives in education, campaigns, awareness, can unlock these potentials of AI/ML in the agriculture and food sector. The policy makers can achieve these by stimulating and innovating partnership between the public-private sector to address the farmers irrespective of their commercial value. These policies can serve as incentives to the development of digital infrastructure in the rural populace by reducing importation charges or dues on precision agricultural extension services, equipment and training. Also, effective partnering amongst governments, private organizations, technology firms, educational institutions, and farmer organizations fosters innovative environments that is supportive of IoT-ML solution. The policy should encourage countries the world over to cooperate and regulate AI in agriculture by standardizing it for inter-country businesses and creativity. Furthermore, it demands an active structure of government ready to collaborate openly with the several stakeholders like those in food sector, local manufacturers, and the newbies. Although, studies indicate that impediments abating collaboration are inadequate or the lack of sharing knowledge about and trust issues.

Future Directions

The future directions of the paper emphasize on the integration of AL/ML with IoT to make available current data absolutely for developing countries with limited agricultural data to enable and enhance speedy response for decisive and meaningful contributions in the region. Also, to help defeat challenges that may arise from inadequate information and encourage collaboration among stakeholders for adoption. This is to ensure that developing economies that engage AI/ML technologies significantly in their agriculture and food sector feed herself while also making positive contribution to the

global food ecosystem. Figure 4 shows the future trends of AI and ML in the agricultural sector.

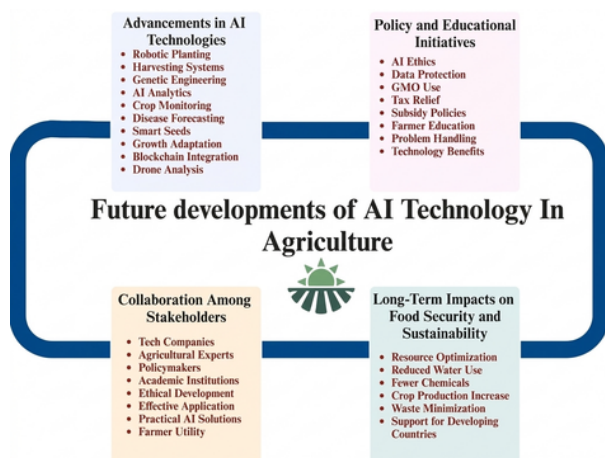


Figure 4. Survey of AI in agriculture [80].

References

1. Zhou ZH. Machine learning. Springer Nature; 2021. <https://doi.org/10.1007/978-981-15-1967-3>
2. Ali SM, Moktadir MA, Kabir G, Chakma J, Rumi MJ, Islam MT. Framework for evaluating risks in food supply chain: implications in food wastage reduction. *J Clean Prod.* 2019;228:786–800. <https://doi.org/10.1016/j.jclepro.2019.04.322>
3. Rejeb A, Keogh JG, Rejeb K. Big data in the food supply chain: a literature review. *J Data Inf Manag.* 2022(1):33–47. <https://doi.org/10.1007/s42488-021-00064-0>
4. Del Borghi A, Gallo M, Strazza C, Del Borghi M. An evaluation of environmental sustainability in the food industry through Life Cycle Assessment: the case study of tomato products supply chain. *J Clean Prod.* 2014;78:121–130. <https://doi.org/10.1016/j.jclepro.2014.04.083>
5. Wakunuma K, Jiya T, Aliyu S. Socio-ethical implications of using AI in accelerating SDG3 in least developed countries. *J Responsib Technol.* 2020;4:100006. <https://doi.org/10.1016/j.jrt.2020.100006>
6. Guo J, Li B. The application of medical artificial intelligence technology in rural areas of developing countries. *Health equity.* 2018;2(1):2018. <https://doi.org/10.1089/heq.2018.0037>
7. Hendler J. Understanding the limits of AI coding. *Science.* 2023;379(6632):548. <https://doi.org/10.1126/science.adg4246>
8. Mazuryk J, Klepacka K, Kutner W, Sharma PS. Glyphosate separating and sensing for precision agriculture and environmental protection in the era of smart materials. *Environ Sci Technol.* 2023;57(27):9898–9924. <https://pubs.acs.org/doi/full/10.1021/acs.est.3c01269>
9. Sridhar HS, Divyashree VP, Keerthana BS, Sushmitha DP. Design and demonstration of IoT and machine learning based smart irrigation system. *AIP Conf Proc.* 2024;3111:030009. <https://doi.org/10.1063/5.0221441>
10. Amir M, Rehman BU, Shahid H, Ali S, Ali F, Bangash KU. Solar forecasting for crop cultivation in peshawar and Mardan regions: a comparative artificial intelligence analysis. *Spectr Eng Sci.* 2025:437–445. <https://doi.org/10.5281/zenodo.15680426>
11. Iqbal N, Shahzad MU, Sherif ES, Tariq MU, Rashid J, Le TV, et al. Analysis of wheat-yield prediction using machine learning models under climate change scenarios. *Sustainability.* 2024;16(16):6976. <https://doi.org/10.3390/su16166976>
12. Sharma V, Tripathi AK, Mittal H. Technological revolutions in smart farming: current trends, challenges & future directions. *Comput Electron Agric.* 2022;201:107217. <https://doi.org/10.1016/j.compag.2022.107217>
13. Lezoche M, Hernandez JE, Díaz MD, Panetto H, Kacprzyk J. Agri-food 4.0: a survey of the supply chains and technologies for the future agriculture. *Comput Ind.* 2020;117:103187. <https://doi.org/10.1016/j.compind.2020.103187>
14. Bačiulienė V, Petrokė I. The impact of artificial intelligence on growth in the agri-food industry: lithuanian case. *Eur Sci.* 2020;2(4):34–40. Available at: <https://epubl.ktu.edu/object/elaba:84121240/>
15. Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D. Machine learning in agriculture: a review. *Sensors.* 2018;18(8):2674. <https://doi.org/10.3390/s18082674>
16. Radocaj D, Jurišić M. GIS-based cropland suitability prediction using machine learning: A novel approach to sustainable agricultural production. *Agronomy.* 2022;12(9):2210. <https://doi.org/10.3390/agronomy12092210>
17. Mao H, Meng J, Ji F, Zhang Q, Fang H. Comparison of machine learning regression algorithms for cotton leaf area index retrieval using Sentinel-2 spectral bands. *App Sci.* 2019 ;9(7):1459. <https://doi.org/10.3390/app9071459>
18. Benos L, Tagarakis AC, Dolias G, Berruto R, Kateris D, Bochtis D. Machine learning in agriculture: a comprehensive updated review. *Sensors.* 2021;21(11):3758. <https://www.mdpi.com/1424-8220/21/11/3758>
19. Goyache F, Bahamonde A, Alonso J, López S, Del Coz JJ, Quevedo JR, et al. The usefulness of artificial intelligence techniques to assess subjective quality of products in the food industry. *Trends Food Sci Technol.* 2001;12(10):370–381. [https://doi.org/10.1016/S0924-2244\(02\)00010-9](https://doi.org/10.1016/S0924-2244(02)00010-9)
20. Hu K. ChatGPT sets record for fastest-growing user base—analyst note. *Reuters.* 2023.
21. Raman CJ. An accurate plant disease detection technique using machine learning. *EAI Endorsed Trans Internet Things.* 2024;10. <https://doi.org/10.4108/eetiot.4963>
22. Liu J, Yang K, Tariq A, Lu L, Soufan W, El Sabagh A. Interaction of climate, topography and soil properties with cropland and cropping pattern using remote sensing data and machine learning methods. *Egypt. J Remote Sens Space Sci.* 2023;26(3):415–426. <https://doi.org/10.1016/j.ejrs.2023.05.005>
23. Botero-Valencia JS, Mejia-Herrera M, Pearce JM. Low cost climate station for smart agriculture applications with photovoltaic energy and wireless communication. *HardwareX.* 2022;11:e00296. <https://doi.org/10.1016/j.johx.2022.e00296>
24. Ranjan P, Garg R, Rai JK. Artificial intelligence applications in soil & crop management. In *2022 IEEE Conf Interdiscip Approaches Technol Manag Soc Innov.* 2022:1–5. <https://doi.org/10.1109/IATMSI56455.2022.10119362>
25. Depuru S, Amala K, Supriya P, Reddy AB, Gireesh RS. VGG-16 technique to reduce the global food crises and enhance the crop yields: deep learning approaches. *3rd Int Conf Appl Artif Intell Comput.* 2024:596–599. <https://doi.org/10.1109/ICAIC60222.2024.10575562>
26. Sen A, Roy R, Dash SR. Smart farming using machine learning and IoT. *Agricultural informatics: automation using the IoT and machine learning.* 2021:13–34. <https://doi.org/10.1002/9781119769231.ch2>

27. Naseem A, Waqas M, Humphries UW. Climate change and food security: Agricultural and non-farm adaptation strategies in Asia. *Climate Change, Food Security, and Land Management*. 2025;1-8.
https://doi.org/10.1007/978-3-031-71164-0_54-1
28. Kovalenko O. Machine learning and AI in food industry solutions and potential—SPD group blog. Full-cycle software development solutions; SPD-group: Seattle, WA, USA. 2022.
29. Sujatha R, Chatterjee JM, Jhanjhi NZ, Brohi SN. Performance of deep learning vs machine learning in plant leaf disease detection. *Microprocess Microsyst*. 2021;80:103615.
<https://doi.org/10.1016/j.micpro.2020.103615>
30. Sharma K, Shivandu SK. Integrating artificial intelligence and internet of things (IoT) for enhanced crop monitoring and management in precision agriculture. *Sens Int*. 2024 ;5:100292.
<https://doi.org/10.1016/j.sintl.2024.100292>
31. Singh D, Biswal AK, Samanta D, Singh V, Kadry S, Khan A, et al. Reracted: smart high-yield tomato cultivation: precision irrigation system using the Internet of Things. *Front Plant Sci*. 2023;14:1239594. <https://doi.org/10.3389/fpls.2023.1239594>
32. Olsen P, Borit M, Syed S. Applications, limitations, costs, and benefits related to the use of blockchain technology in the food industry. Available at:
<https://agris.fao.org/search/en/providers/125328/records/6748e2277625988a37218541>
33. Fortuna F, Risso M. Blockchain technology in the food industry. *Symphonya Emerg Issues Manag*. 2019;2:151-158.
<http://dx.doi.org/10.4468/2019.2.13>
34. Patelli N, Mandrioli M. Blockchain technology and traceability in the agrifood industry. *J Food Sci*. 2020;85(11):3670-3678.
<https://doi.org/10.1111/1750-3841.15477>
35. Antonucci F, Figorilli S, Costa C, Pallottino F, Raso L, Menesatti P. A review on blockchain applications in the agri-food sector. *J Sci Food Agric*. 2019;99(14):6129-6138.
<https://doi.org/10.1002/jsfa.9912>
36. Shahbazi Z, Byun YC. A procedure for tracing supply chains for perishable food based on blockchain, machine learning and fuzzy logic. *Electronics*. 2020;10(1):41.
<https://doi.org/10.3390/electronics10010041>
37. Polonsky JA, Baidjoe A, Kamvar ZN, Cori A, Durski K, Edmunds WJ, et al. Outbreak analytics: a developing data science for informing the response to emerging pathogens. *Philos Trans R Soc B Biol Sci*. 2019;374:1776.
<https://doi.org/10.1098/rstb.2018.0276>
38. Wang H, Cui W, Guo Y, Du Y, Zhou Y. Machine learning prediction of foodborne disease pathogens: algorithm development and validation study. *JMIR Med Inform*. 2021;9(1):e24924. <https://doi.org/10.2196/24924>
39. Van Boekel MA. Kinetics of heat-induced changes in dairy products: developments in data analysis and modelling techniques. *Int Dairy J*. 2022;126:105187.
<https://doi.org/10.1016/j.idairyj.2021.105187>
40. Zhu LY, Yan L, Zhao F, Guo X, Xu D, Lv J, et al. Evaluation of methods for the detection of hazardous substances in food based on machine learning. *New J Chem*. 2024;48(3):1399-1406.
<https://doi.org/10.1039/D3NJ04074G>
41. Astuti SD, Tamimi MH, Pradhana AA, Alamsyah KA, Purnobasuki H, Khasanah M, et al. Gas sensor array to classify the chicken meat with *E. coli* contaminant by using random forest and support vector machine. *Biosens Bioelectron*: X. 2021;9:100083. <https://doi.org/10.1016/j.biosx.2021.100083>
42. Fu B, Labuza TP. Shelf-life prediction: theory and application. *Food control*. 1993;4(3):125-133.
[https://doi.org/10.1016/0956-7135\(93\)90298-3](https://doi.org/10.1016/0956-7135(93)90298-3)
43. Martinez-Castillo C, Astray G, Mejuto JC, Simal-Gandara J. Random forest, artificial neural network, and support vector machine models for honey classification. *EFood*. 2020;1(1):69-76.
<https://doi.org/10.2991/efood.k.191004.001>
44. de Santana FB, Neto WB, Poppi RJ. Random forest as one-class classifier and infrared spectroscopy for food adulteration detection. *Food chem*. 2019;293:323-332.
<https://doi.org/10.1016/j.foodchem.2019.04.073>
45. Saha D, Manickavasagan A. Machine learning techniques for analysis of hyperspectral images to determine quality of food products: a review. *Curr Res Food Sci*. 2024;4:28-44.
<https://doi.org/10.1016/j.crfs.2021.01.002>
46. Cervantes-Godoy D. Aligning agricultural and rural development policies in the context of structural change. 2022;187:39.
<https://doi.org/10.1787/1499398c-en>
47. Mukherjee AN. Application of artificial intelligence: benefits and limitations for human potential and labor-intensive economy—an empirical investigation into pandemic ridden Indian industry. *Manag Matters*. 2022;19(2):149-166.
<https://doi.org/10.1108/MANM-02-2022-0034>
48. BIS Research, 5e Rising demand for agriculture drones and robots, BIS Research, Fremont, CA, USA, 2021.
<https://blog.marketresearch.com/the-rising-demand-for-agriculture-drones-and-robots>
49. Farrelly Mitchell. Blockchain in Agriculture: Solving Agri-Food Supply Chain, Dubai, UAE, 2020.
<https://farrellymitchell.com/blockchain-in-agriculture-solving-food-supply-chain/>
50. Akkem Y, Biswas SK, Varanasi A. Smart farming using artificial intelligence: a review. *Eng Appl Artif Intell*. 2023;120:105899.
<https://doi.org/10.1016/j.engappai.2023.105899>
51. Reddy DJ, Kumar MR. Crop yield prediction using machine learning algorithm. In 2021 5th Int Conf Intell Comput Control Syst. 2021:1466-1470.
<https://doi.org/10.1109/ICICCS51141.2021.9432236>
52. Padhiary M. The convergence of deep learning, IoT, sensors, and farm machinery in agriculture. *Des Sustain Internet Things Solut Smart Ind*. 2025;109-142.
<https://doi.org/10.4018/979-8-3693-5498-8.ch005>
53. Haydar Z, Esau TJ, Farooque AA, Abbas F, Fraser A. Integration of machine learning models with real-time global positioning data to automate the wild blueberry harvester. *Precis Agric*. 2025;26(1):7.
<https://doi.org/10.1007/s11119-024-10204-2>
54. Maitra A, Damle M. Revolutionizing plant health management with technological digital transformation to enhance disease control & fortifying plant resilience. In 2024 3rd Int Conf Innov Technol. 2024: 1-8.
<https://doi.org/10.1109/INOCON60754.2024.10511728>
55. Pham X, Stack M. How data analytics is transforming agriculture. *Bus Horiz*. 2018;61(1):125-133.
56. Pray C, Daum T, Birner R. Who drives the digital revolution in agriculture? a Review of supply-side trends, players and challenges. 31st ICAE. 2021.
<https://doi.org/10.1002/aep.13145>
57. LeMieux J. From Pharma to Farm Can CRISPR Feed the World? Now in its second decade, CRISPR genome editing technology is being used to revolutionize agriculture—just in time to help us adapt to climate change. *Genet Eng Biotechnol News*. 2022;42(6):32-36.
<https://doi.org/10.1089/gen.42.06.12>

58. Kock MA. Intellectual property protection for plant related innovation. Springer, Cham. 2022;10:978-983.
<https://doi.org/10.1007/978-3-031-06297-1>
59. Kirpach M, Riccoboni A. AI in agriculture. Eng Math Artif Intell. 2023;331-364. Available at:
<https://www.taylorfrancis.com/chapters/edit/10.1201/9781003283980-14/ai-agriculture-marie-kirpach-adam-riccoboni>
60. Misra NN, Dixit Y, Al-Mallahi A, Bhullar MS, Upadhyay R, Martynenko A. IoT, big data, and artificial intelligence in agriculture and food industry. IEEE Internet Things J. 2020;9(9):6305-6324.
<https://doi.org/10.1109/JIOT.2020.2998584>
61. Food Safety & Quality. Available online:
<https://www.tetrapak.com/sustainability/focus-areas/food-safety-quality> (accessed on 1 August 2024).
62. Tiwari A, Jaga PK. Precision farming in India-A review. Outlook on Agriculture. 2012;41(2):139-143.
<https://doi.org/10.5367/oa.2012.0082>
63. Rana MM. Conservation agriculture for sustainable crop productivity and economic return for the smallholders of Bangladesh: a systematic review. Turk J Agric Food Sci Technol. 2023;11(10):2009-2015.
<https://doi.org/10.24925/turjaf.v11i10.2009-2015.6053>
64. Shaktawat P, Swaymprava S. Digital agriculture: exploring the role of information and communication technology for sustainable development. Ed. Biswajit Mallick and Jyotishree Anshuman published by PMW, New Delhi. 2024;31. Available at:
https://www.researchgate.net/profile/Biswajit-Mallick-3/publication/375417847_Navigating_Agricultural_Extension_A_Comprehensive_Guide/links/6549a336b86a1d521bbfd893/Navigating-Agricultural-Extension-A-Comprehensive-Guide.pdf#page=40
65. Pye-Smith C. How farmers are making the most of digital technologies in East Africa: Stories from the field. 2018. Available at:
<https://cgspace.cgiar.org/items/Od36f6ae-d4de-4976-b43c-9be9ab0a2226>
66. Apraku A, Morton JF, Gyampoh BA. Climate change and small-scale agriculture in Africa: does indigenous knowledge matter? Insights from Kenya and South Africa. Sci Afr. 2021;12:e00821.
<https://doi.org/10.1016/j.sciaf.2021.e00821>
67. Awuor F, Kimeli K, Rabah K, Rambim D. ICT solution architecture for agriculture. In 2013 IST-Africa Conf Exhib 2013: 1-7. Available at:
<https://ieeexplore.ieee.org/abstract/document/6701752>
68. Mark R. Ethics of using AI and big data in agriculture: the case of a large agriculture multinational. Orbit J. 2019;2(2):1-27.
<https://doi.org/10.29297/orbit.v2i2.109>
69. Cumming D, Saurabh K, Rani N, Upadhyay P. Towards AI ethics-led sustainability frameworks and toolkits: review and research agenda. J Sustain Finance Account. 2024;1:100003.
<https://doi.org/10.1016/j.josfa.2024.100003>
70. Sakthivel V, Prakash P, Prabu P. Enhancing Transparency and trust in agrifood supply chains through novel blockchain-based architecture. KSII Trans Internet Inf Syst. 2024;18(7).
<https://doi.org/10.3837/tiis.2024.07.013>
71. Ahanger TA, Ullah I, Algamdi SA, Tariq U. Machine learning-inspired intrusion detection system for IoT: security issues and future challenges. Comput Electr Eng. 2025;123:110265.
<https://doi.org/10.1016/j.compeleceng.2025.110265>
72. Treinen S, Van der Elstraeten A. Gender and ICTs- Mainstreaming gender in the use of information and communication technologies (ICTs) for agriculture and rural development. Gender ICTs: Mainstreaming Gender Use Inf. Commun Technol Agric Rural Dev 2018. Available at:
https://d1wqtxts1xzle7.cloudfront.net/100233326/18670EN-libre.pdf?1679678490=&response-content-disposition=inline%3B+filename%3DGender_and_ICTs_Mainstreaming_gender_in.pdf&Expires=171999045&Signature=UvJPllkwC6inxWk761oNciBO9ttu4b0cH488wmohjSr2FICUjHiQebGU5PXcJRa9qtePhORwJORZEY~kRQqxMEkGZ~7Zwwec8w4yTlvBglIN8REGIzbjnmObLLneGPq7IQTqmU6dppUG4VoTe0XcsRdE6S6hYudWw5OymTSZ7S286ucGxQNze3JqFJnWmgc0JGqnNKvS0mgld-C-lcB6ESeMVpxlaipqleNK-4hSvII-ZtwtlTK-bh8nqj6Wdx0KKuamA6oopST-i-1G5dcESgXxL7tflkEVRpOUnegi0DU4MZM7wliGiHIDstEt4UvE2y5FFJi3F-la5MSny59Q...&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA
73. Ghosh A, Chakraborty D, Law A. Artificial intelligence in Internet of things. CAAI Trans Intell Technol. 2018(4):208-218.
<https://doi.org/10.1049/trit.2018.1008>
74. Charania I, Li X. Smart farming: agriculture's shift from a labor intensive to technology native industry. Internet Things. 2020;9:100142. <https://doi.org/10.1016/j.iot.2019.100142>
75. Redhu NS, Thakur Z, Yashveer S, Mor P. Artificial intelligence: a way forward for agricultural sciences. Bioinform Agric. 2022;641-668.
<https://doi.org/10.1016/B978-0-323-89778-5.00007-6>
76. Ryan M. The social and ethical impacts of artificial intelligence in agriculture: mapping the agricultural AI literature. Ai Society. 2023;38(6):2473-2485.
<https://doi.org/10.1007/s00146-021-01377-9>
77. Belcher JW. Farmer adoption of advanced technology in agribusiness (Doctoral dissertation, University of South Florida). 2022. <https://doi.org/10.2307/30036540>
78. Gill GS. ICT and issues in Indian agriculture. Int J Adv Res Eng Technol. 2021;12(6):95-100.
<https://doi.org/10.34218/IJARET.12.6.2021.009>
79. Amusan L, Akokuwebe ME, Odularu G. Women development in agriculture as agency for fostering innovative agricultural financing in Nigeria. <https://doi.org/10.18697/ajfand.102.19345>
80. Aijaz N, Lan H, Raza T, Yaqub M, Iqbal R, Pathan MS. Artificial intelligence in agriculture: a crop productivity and sustainability. J Agric Food Res. 2025;20:101762.
<https://doi.org/10.1016/j.jafr.2025.101762>
81. Maraveas C. Incorporating artificial intelligence technology in smart greenhouses: Current State of the Art. Appl Sci. 2022;13(1):14. <https://doi.org/10.3390/app13010014>
82. Balraj PL, Pavalam SM. Integrating ICT in agriculture for knowledge-based economy. Rwanda J. 2012;27:44-56.
<https://doi.org/10.4314/rj.v27i1.5>
83. Lundström C, Lindblom J. Considering farmers' situated knowledge of using agricultural decision support systems (AgriDSS) to foster farming practices: the case of CropSAT. Agric Syst. 2018;159:9-20.
<https://doi.org/10.1016/j.agsy.2017.10.004>
84. Dhaka BL, Chayal K. Farmers' experience with ICTs on transfer of technology in changing agri-rural environment. Indian Res J Ext Educ. 2010;10(3):114-118. Available at:
<https://api.seea.org.in/uploads/pdf/v10321.pdf>

85. Javaid M, Haleem A, Singh RP, Suman R. Substantial capabilities of robotics in enhancing industry 4.0 implementation. *Cogn Robot*. 2021;1:58-75. <https://doi.org/10.1016/j.cogr.2021.06.001>
86. Khanthachai N. World Bank. World Development Report 2019: the changing nature of work.(2019). <http://www.worldbank/en/publication/wdr2019>. Kasem Bundit J. 2020;21(2):211-214. Available at: <https://so04.tci-thaijo.org/index.php/jkbu/article/view/247971>
87. Dhal SB, Kar D. Leveraging artificial intelligence and advanced food processing techniques for enhanced food safety, quality, and security: a comprehensive review. *Discov Appl Sci*. 2025;7(1):75. <https://doi.org/10.1007/s42452-025-06472-w>
88. Gupta M, Abdelsalam M, Khorsandroo S, Mittal S. Security and privacy in smart farming: challenges and opportunities. *IEEE access*. 2020;8:34564-34584. <https://doi.org/10.1109/ACCESS.2020.2975142>
89. Sonka ST. Farming within a knowledge creating system: biotechnology and tomorrow's agriculture. *Am Behav Sci*. 2001(8):1327-1349. <https://doi.org/10.1177/00027640121956845>