OPEN ACCESS PEER REVIEW
DOI: https://doi.org/10.52756/ bhstiid.2024.e01.005

Chapter- 5

Integration of artificial intelligence toward better agricultural sustainability

Mayuri Bhagawati*, Chayan Dhar, Dipan Sarma, Manna Das, Badal Kumar Datta

Keywords: Agriculture, Artificial Intelligence (AI), Sustainability, Agroecology, Agribots.

Abstract:

The development and even survival of human civilization is highly dependent on agriculture. Modern human society, with a vast population, is continuously pressurizing agricultural techniques to modify themselves in a way that satisfies the hunger of this rapidly growing population. To ensure food security, several methods and chemical inputs have been applied in the field of farming which disturb their average ecological balance, reduce the nutrient content in the food, affect the average fertility of the soil, cause overexploitation of the natural resources, and even responsible for various fatal health issues in humans. Thus, an alternative resolution is needed, which is Artificial Intelligence. Integration of AI has proved to be a boon for the present-day farmers. AI eases farming practices by monitoring crop health, predicting pests, diseases, drought, weather forecasting, harvesting, categorizing harvested ones, aiding farmers in making necessary decisions regarding selling, etc. They also facilitate sustainability as early prediction of weeds, pests, and diseases would directly reduce the content of chemical inputs in the field; this, in turn, supports soil health and also checks overexploitation of groundwater while irrigating the croplands. Except for the doubt and misconceptions of the farmers about the potency of these AI-based tools in fulfilling their needs and the high cost, AI as a whole is a complete solution to the modern farming society for benefiting themselves and fulfilling the market demand without disturbing our ecosystem.

Introduction:

The role of agriculture in the developing human society is peerless. But the requirement of society is rising tremendously day by day along with drastically enhancing population, which ultimately compels the traditional agricultural systems to transform themselves into modernized methodologies that employ noxious chemical fertilizers, pesticides, weedicides, high-tech machines, and so on. While fulfilling the needs of the exploding population, the modern

Mayuri Bhagawati*
[1]Department of Botany, Tripura University (A Central University) Suryamaninagar – 799022, Tripura
E-mail: mayuribot13@gmail.com; Orcid iD: https://orcid.org/0000-0003-3940-6828
Chayan Dhar
[1]Department of Botany, Tripura University (A Central University) Suryamaninagar – 799022, Tripura
Dipan Sarma
[1]Department of Botany, Tripura University (A Central University) Suryamaninagar – 799022, Tripura
[2]Department of Botany, Govt. Degree College, Dharmanagar-799253, Tripura
E-mail: dipanphd@gmail.com; Orcid iD: https://orcid.org/0000-0002-5643-6327
Manna Das
[2]Department of Botany, Govt. Degree College, Dharmanagar-799253, Tripura
E-mail: arkaprabhapal0610@gmail.com
Badal Kumar Datta
[1]Department of Botany, Tripura University (A Central University) Suryamaninagar – 799022, Tripura
***Corresponding Author**: mayuribot13@gmail.com & dipanphd@gmail.com

Dr. Suman Adhikari, Dr. Manik Bhattacharya and Dr. Ankan Sinha, A Basic Handbook of Science, Technology and Innovation for Inclusive Development [Volume: 1]. ISBN: 978-81-969828-4-3; pp- 71-85; Published online: 27th May, 2024

farming society has become highly dependent on modern technologies and chemical inputs, and sustainability is merely unnoticed (Mohan et al., 2023). This dependency of agriculture on modern methods ultimately radiates its adverse effects on the abiotic components of the ecosystem as well as on the biota belonging to the agroecosystem and even biomagnified to wider audiences, i.e., the consumers (Sarkar et al., 2016; Ray, 2019; Banerjee et al., 2021). The introduction of precision agriculture has also proved to be a boon in this field. Intellectual solutions provided by artificial intelligence have been implemented in recent years in the field of agriculture to develop methods that boost productivity by considering problems, predicting pests, calamities, and crop maturation, specifying chemical inputs, managing weeds, optimizing resource utilization, and many more (Talaviya et al., 2020; Rozaini et al., 2023; Chaudhary et al., 2023; Dawn et al., 2023). Early prediction and specification of chemical inputs lead to their minimal use in this field, enhancing sustainability (Raj et al., 2023). The perfect balanced use of high-tech sensors and analytical tools contributed by AI and their alliance with the principles of agroecology can potentially solve a lot of modern problems to achieve sustainable agriculture (Sasso et al., 2021; Cousin et al., 2021; Rout and Samantaray, 2022). The contemporary initiative of involving the intellect of artificial intelligence in the field of farming aids in real-time monitoring, control, and automation. Various wireless sensors acquire information on various environmental parameters like soil moisture, temperature, humidity, and other factors. Technologies such as drones, GPS, farm automation, robots, etc., directly aid in agricultural mapping, soil analysis, geospatial data access, resource monitoring, management, crop health monitoring, chances of success or failure of crops, calamities, and many more. These datasets help the AI make necessary decisions based on these crucial parameters. Critical decisions include sowing, fertilizer, pesticide and weedicide applications, irrigation, harvesting, market analysis, distribution, etc.

Green Revolution in the Agricultural Sectors:

The term green revolution is used to describe the agricultural revolution of the 1960s. During the mid-20th century, the world, especially the undeveloped countries, needed agricultural stability. This goal is achieved by introducing genetically modified crop varieties such as HYV, mechanization, better irrigation facilities, and chemical inputs such as pesticides, fertilizers, and so on (Somvanshi and Singh, 2020). Green Revolution became a savior for those who were under poverty levels or were under threat of falling into poverty levels in the coming years. The achievements of the Green Revolution are remarkable and include increased productivity, benefits farmers by boosting income and food security, the introduction of technologies that make farming easier, economic strengthening of developing and underdeveloped countries, and many more (Pingali, 2012).

Negative effects of agricultural modernization:

The inevitable detrimental consequences of modernized agricultural practices must be mentioned to understand how they are affecting the ecosystem, health, and some other fields.

Biomagnification of harmful chemical pesticides, fertilizers, and weedicides to higher ecosystem trophic levels is a common side effect of modern agriculture. Biomagnification and subsequent bioaccumulation of these pollutants are very serious issues to deal with. Nearly 42% decline in species richness was observed within the last 30-40 years in Europe. In humans, exposure to these contaminants can directly or indirectly affect health by inducing different types of cancers like leukemia, lymphoma, and brain cancer (Ali et al., 2021). Also, the continuous demand for crop production needs a large land area for production, which directly leads to a decline, i.e., destruction of natural habitats by up to 47% which in turn stimulates land degradation, soil erosion, extinction of diversity of crop or wild varieties, negate adaptivity, evolutionary potential and enhances vulnerability (Somvanshi and Singh, 2020; Lopez et al., 2022). Many authors also highlight the serious issue of crop genetic erosion to help us understand that the cultivation of only particular highly yielding varieties of crops is destroying the great varieties of germplasms that are getting lost due to their underutilization in the agricultural sector. In addition, modernization also negatively affects traditional agricultural knowledge utilization (Khoury et al., 2022).

Need for an alternative solution:

The limitations of modern agricultural methodologies enhanced the urge of the researchers to develop a way of agriculture that boosts productivity with minimum effect on the environment. For this, thoughtful consideration of all the fields that are directly or indirectly influenced by them should be done. The assessment of environmental, medical, traditional, and all other fields that are affected by modern techniques and chemical pesticides was done in the last few decades to construct a practicable solution to abate their fatal effects with minimal efforts and by not compromising the benefit, economic stability of the global farming society. The utility of modern techniques and chemical inputs can't be totally stopped, but they can surely be reduced to a considerable amount to avoid its deleterious aftermath.

Transformative approaches: Solutions:

A practicable solution is extensively needed for achieving sustainable agriculture and promoting healthy and disease-free lifestyles. The negative consequences of modernized agricultural practices are, in turn, countered by practically employing the intellect of artificial intelligence. This alternative path can effectively meet the continuously growing global demands for food without pressurizing the agroecosystem.

Smart agricultural approach:

The re-establishment of the devastated ecosystem of the croplands is highly desirable to avoid more severe environmental hazards. Precision farming has become the soul of smart, sustainable agriculture. It involves using technologies such as sensors, GPS, drones, data analytics, IoT, ICT, and AI to achieve sustainable and profitable agricultural practices. Both the Internet of Things (IoT) and Artificial Intelligence (AI) are the most trusted platforms for the advancement of smart agricultural practices. IoT is a versatile technology integrating highly intellectual devices within a single global network: the Internet. Implementation of IoT has proven to be highly reliable. Implementation of IoT-mediated automatic irrigation system is a specified technique that proves that their implementation in the agricultural sector is highly justified. IoT in this sector also plays a great role in agricultural product management. Thus, it is vital in both production and post-production activities (Alreshidi, 2019). The smart and multidisciplinary technology of AI implies a branch of computer science that deals with the production of devices that mimic human intelligence in performing tasks and involve deep learning, machine learning, etc. (Raj et al., 2022). Different Artificial intelligence algorithms were integrated into the field of agriculture for the fulfillment of certain desired goals. Oliveira et al., 2021 highlighted that AI-based algorithms MLP, CNN, R-CNN, R-YOLO, and SVM aid in disease detection, weed detection, selection of specific weedicide, location of plant products and its qualitative assessment like ripening, and assessment of yield. ANN algorithms were reported to be widely applied as predictive AI models (Liu et al., 2020; Liu et al., 2021; Buyrukoglu et al., 2021) and can be implemented in weed controlling (Monteiro et al., 2021), managing water (Alvim et al., 2022), pest management (Markovic et al., 2021). Robotics is another highly applied technology in the agricultural field. It is highly interconnected with AI to boost its intellectual properties for proper decision-making, deep learning, change adaptation, etc. Integration of robots for the purpose of agricultural modification and sustainability is a very popular approach in modern times (Azmi et al., 2021; Unal et al., 2021; Ghafar et al., 2021; Roshanianfard et al., 2021; Hespeler et al., 2021). Adhikari et al., 2022 claimed that CNN reflects very high performance in flood predictions, whereas, for drought forecasting, the performance of WANFIS is remarkable. Also, they pointed out that the climatic conditions of a particular area have almost no effect on these models. Zhang et al., 2021 employed Multiple Linear Regression (MLR), Long Short-Term Memory (LSTM), and Random Forest (RF) models to evaluate the Rate of Intensification (RI) and flash drought monitoring. The probability of Detection (POD), False Alarm Ratio (FAR), and Critical Success Index (CSI) of flash drought derived from RF were 0.93, 0.15, and 0.80, respectively for the RF model which reveals its enhanced potency to achieve the respective goals compared to the other two AI models. By employing ANN models, Liu et al., 2020 successfully prepared the integrated agricultural drought index to predict the risk of upcoming drought. Liu et al., 2021 mentioned the successful implementation of artificial neural networks, regression algorithms, and gene-expression programming for predicting the growth rate of rice on the basis of the ambient temperature of warm regions. The authors also pointed out that the ANN models are better, even not wrong, to mention best in comparison to the other 2 models. Similarly, Buyrukoglu et al., 2021 predict the population of Generic *E. coli* based on the Weather Station Measurements by using ANN and some other models. Almomani et al. (2020) successfully employed the ANN algorithms for the prediction of aerobic digestion, i.e., the production of biogas from the wastes generated by agricultural sectors. Besides ANN various other AI models were also employed for the predictive purposes. Malhotra and Firdaus, 2022 highlighted using AI-based predictive models for yield prediction. Laktionov et al., 2023 reported the use of Explainable Artificial intelligence models (XAI) for the purpose of monitoring and predicting the diseases of corn. Jain and Ramesh., 2021 successfully utilized CNN-LSTM models for the preparation of pest prediction and classification model for yellow stem border disease in Rice. Artificial Neural Networks, Random Forest, and Multiple Linear Regression algorithms were taken into account by Silva et al., 2024 for predicting the yield as well as the quality of carrots.

Table 1. Various applications and achievements of different AI technologies.

Sl no.	AI model/ technology	Applications	Achievements	References
1	Artificial Neural Network	Growth Prediction of Carrot	Mean of accuracy i.e., R^2 = 0.68	Silva et al., 2024
2	Convolutional Neural Network	Identification of plant diseases	93.75% accuracy	Chen et al., 2021
3	ANN	The growth rate of rice	R^2 =0.99	Liu et al., 2021
4	Adaptive Neuro-Fuzzy Inference System	Early prediction of disease in corn (Fusarium Head Blight, Southern Corn Leaf blight, Northern Corn Leaf blight.	The R^2 value is 0.96, 0.75, 0.8 for FHB, SCLB, and NCLB, respectively.	Laktionov et al., 2023
5	CNN-AlexNet with PSO Optimization.	Detecting plant disease in 5 crops (Wheat, cotton, grape, corn, cucumber)	Specificity 98.56%, accuracy 98.83%, sensitivity 98.78%, precision 98.67% and F score 98.47%	Elaraby et al., 2022.
6	YOLOv5s, YOLOv5m and YOLOv5l	Detection of weeds in wheat fields.	Precision is 0.59, 0.67, 0.84 and F-score is 0.51, 0.57, and 0.54 for YOLOv5s, YOLOv5m, and YOLOv5l, respectively.	Haq et al., 2023
7	Random Forest	Rate of Intensification and Flash Drought Monitoring	POD, FAR, and CSI of flash drought derived from RF were 0.93, 0.15, and 0.80 respectively	Zhang et al., 2021
9	ANN-MLP	Weed control and crop-	Accuracy 0.98, precision	Monteiro et

		weed competition modeling.	0.94, and F score 0.98	al., 2021
10	Long Short-Term Memory	Prediction of irrigation water and energy necessity to achieve optimum water use efficiency as well as yield.	R^2 between 0.90 - 0.92	Mohammed et al., 2023
11	ANN	Prediction of Generic *E. coli* population.	Mean Absolute Error values range between 0.87-46.6	Buyrukoglu et al., 2021
12	Mask R-CNN and YOLOv5	Identification and quality detection of apples, bananas, oranges, and tomatoes.	mAP values for quality detection models of apple, banana, orange, and tomato are 99.6, 93.1, 96.7, and 95%, respectively.	Goyal et al., 2023
13	ML	Prediction of pests like *Helicoverpa armigera*	76.5% accuracy but with the extension of five days, accuracy increased to 86.3%, and the percentage of false detection was 11% only.	Markovic et al., 2021
14	Zero sheet transfer learning (Fine-tuned VGG-16 network)	Fruit ripe and unripe prediction	Accuracy range between 70-82.	Dutta et al., 2023
15	CNN with fuzzy C means segmentation.	Detection and classification of diseases in banana plants.	Accuracy 93.45%.	Krishnan et al., 2022
16	ML, YOLO v 4 (You Only Look Once v4)	Yield prediction and detection of *Citrus* fruit.	24% reduction in error.	Vijayakumar et al., 2021
17	ML (Machine Learning)	Sorting and categorizing of fruits based on ripe,or unripe, i.e., grading.	95% accuracy	Chopra et al., 2021
18	CNN, VGG 16, VGG 19, ResNet,	Detection of leaf disease in tomato.	Inception V3 has the highest accuracy 85 and 93.7 by	Ahmad et al., 2020

	Inception V3		feature extraction and parameter tuning of field data. It also has the highest precision and F1 score 0.845, and 0.87 respectively.	
19	CNN-AlexNet	Classification and modeling for leaf disease in maize.	99.16 % accuracy	Singh et al., 2022
20	ANN	Integrated agricultural drought index preparation	Not mentioned	Liu et al., 2020
21	CNN+ LSTM	Predicting rainfall and monitoring fruit health	89.38% accuracy, 0.316 loss score of rainfall prediction.	Kaplun et al., 2024
22	PCA with whale optimization algorithm and DNN	Tomato crop disease classification.	94% testing accuracy and 99% training accuracy.	Gadekallu et al., 2021
23	CNN and AlexNet	Fruit maturity classification and detection of quality.	98.25 and 81.75 % accuracy for CNN and AlexNet, respectively.	Aherwadi et al., 2022
24	AI and 6G-IoT	Smart agricultural irrigation system development	Accuracy 86.34%, Sensitivity 89.28% and Precision 91 %.	Sitharthan et al., 2023
25	CNN	Identification of tomato leaf disease	98.4% accuracy	Agarwal et al., 2020.
26	CNN integrated with attention strategy.	Infection detection in tomato leaves	98% accuracy	Karthik et al., 2020
27	Recursive architecture based on neural networks (RNN)	Prediction of disease and monitor farm.	Precision, specificity, accuracy, and F1-score are 89%, 89%, 96%, and 75%, respectively.	Wongchai et al., 2022

Sustainability achievements through AI-based agricultural approaches:

Today's modern world is highly curious to understand and solve each and every problem in more or less in every field. From the middle of the 20th century, the serious issue of agricultural development, i.e., enhancing yield, profit margins, food safety, and security, was considered, and the solutions suggested by scientists throughout the world were applied. As a result, the present scenario of the global agricultural sector is much better than earlier. Still, the methods employed to stabilize farming, in turn, weaken the stability and disturb the normal functioning of the ecosystem, decrease the levels of natural resources, and also reflect its negative consequences on human life. According to FAO World Food and Agriculture – Statistical Yearbook 2023, 27% i.e., 830 million of the world's population is dependent on agriculture for their livelihood in the year 2021 and the whole world is dependent on this sector for food i.e. survival. So, the yield-enhancing factors cannot be compromised at all as they will directly influence food security, but it is necessary to understand and find out which yield-enhancing factors are having deteriorating effects on the ecosystem and how their negative effects can be minimized.

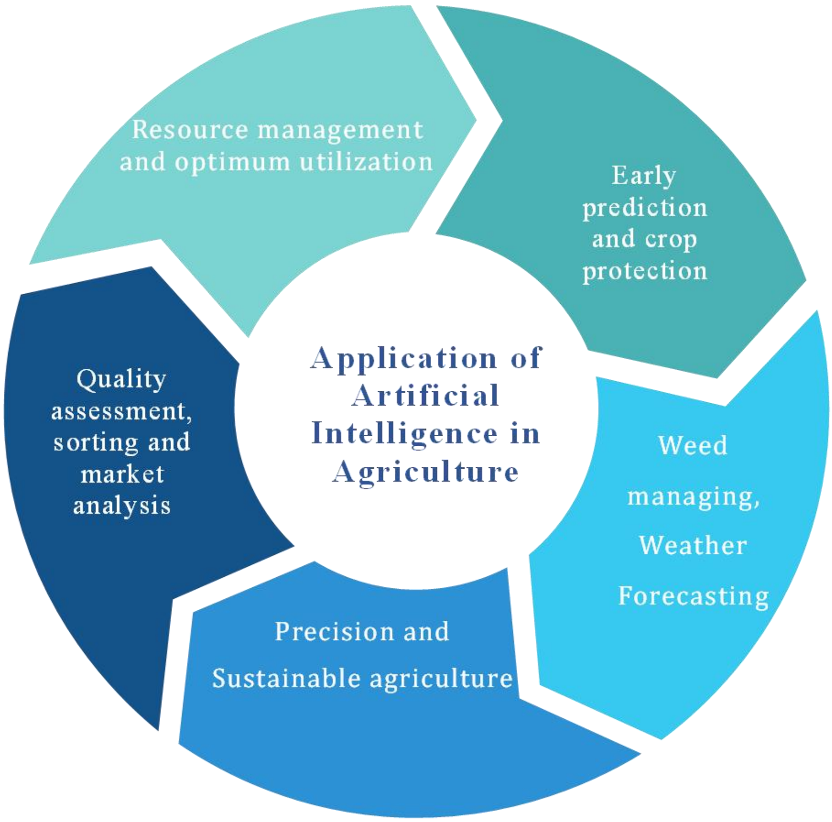

Figure 1. Application of AI tools in agriculture

Early Prediction:

The most common application of artificial intelligence is prediction. The predictive analysis is essential to precisely predict sowing time, harvesting time, pest attack, chances of diseases, market analysis, and price-related factors for specific crops. Artificial Neutral Networks is a specific type of AI technology commonly employed to predict different parameters. According to the United Nations FAO World Food and Agriculture – Statistical Yearbook 2023, the global use of pesticides up to 62% within just 2000-2021, and 56%, i.e., 195 million tonnes of inorganic N_2 were utilized within 2021. Specific steps must be taken to control and minimize the application of more chemical inputs in agricultural systems. Early detection, i.e., predicting diseases and stresses like drought before their arrival, can help farmers apply the resources wisely and minimize the use of pesticides. As disease is predicted earlier, farmers can be able to adopt steps that can minimize the chances of pest attack or disease spread. The synergism and integration of AI for prediction-based sustainability goal enhancement are reported (Wongchai et al., 2022). It is claimed that early prediction of pests in the cropland by employing ML models like AdaBoost, K-Nearest Neighbors, Decision Tree, Neural Net, and Poly SVM can allow the farmers to take necessary steps to check the attack, minimize the use of harmful insecticides by developing better alternative protective measures (Markovic et al., 2021).

Resource Management and Optimum Utilization:

Management and analysis of natural resources like water and soil are crucial for increasing growth, avoidance of stress, and boosting crop productivity along with sustainability by decreasing the chance of over-irrigation, soil erosion, etc. Many authors have pointed out AI-mediated resource management, such as Jez et al., 2021; Elbeltagi et al., 2022; Awais et al., 2023. According to the United Nations World Water Development Report (2023), about 25% of the groundwater has been withdrawn for the purpose of irrigating cropland. Areas with high irrigation and urbanization witnessed high levels of water scarcity. This problem can arise further if an alternative approach is not taken. This competition between cities and the agricultural sector withdraws nearly 72% of the global freshwater. This decline in the water level is so high that if it's controlled or water use is not reduced, the world may witness a water crisis that will be highly destructive for the survival of humanity.

AI-based Machine learning and deep learning technologies for successful soil texture assessment and soil water content analysis. AI-based technology monitoring is much easier, beneficial, and time-saving compared to commonly applied soil parameter measuring techniques and thus supports real-time decision-making (Awais et al., 2023). Algorithms based on Convolutional Neural Networks to predict the yield and also for advanced irrigation management is employed. Scientists used the term smart irrigation, which implies the precise, sustainable use of water resources to fulfill the requirement of crop plants to achieve high yields. They also pointed out that these AI-mediated methods, along with other components, are highly beneficial in decreasing the unnecessary use of water and energy (Sinwar et al., 2020). Also, these highly intellectual devices efficiently aid in reducing the load on the human brain for agricultural planning and other human efforts. Mohammed et al. (2023) highlighted that LSTM and XGBoost can accurately predict the need for water and energy in agricultural systems. These two models were successfully exploited to achieve the goal of sustainable irrigation in arid areas where the availability of water is a great deal. Since preserving water is a highly essential synergistic approach of utilizing the intellect of AI-based algorithms to ensure minimum water use with an extremely low rate of water wastage for achieving optimum growth, it is a great approach towards sustainable agriculture. It is also pointed out that the use of AI is a practicable solution for managing water resources, studying the optimum water level required by the plants, and boosting yield (Alvim et al., 2022).

AI-mediated Agroecology: A Sustainable Approach towards Automated Agroecology:

Over-exploitation of nature and natural resources and continuous devastation of the environment by using chemical inputs ultimately led to the introduction of new disciplines naming agroecology that not only studies the effect of these toxicities on the health of crops, cropland, and the biota directly or indirectly related to the agroecosystem but also suggests a practicable solution to maintain sustainability and regenerate traditional methods to enhance production for the fulfillment to needs of a growing market, minimized external resource utilization, maintains a balance within the agricultural ecosystems and thus enhancing agricultural sustainability. Agroecology is a transformative, integrated, or transdisciplinary approach that combines traditional agricultural knowledge with the principles of ecology to fulfill its ultimate goal of agricultural sustainability. It also involves the study of interactions and the interrelationships between different biotic communities residing in their respective agrobiology; it also considers the effects of environmental conditions on these communities and their respective effects on production (Seremesic et al., 2021). Many authors have previously reported the synergistic approach of combining the intellect of AI with the principles of agroecology (Rout and Samantaray., 2022; Cousin et al., 2021). One successful example of AI-integrated agroecological management in Brazil. Artificial intelligence algorithms were applied to create the Species distribution models. These models were created by combining the intellect of AI with the georeferenced programming techniques and the combined data from the Global Biodiversity Information Facility (GBIF), WORLDCLIM, and ENVIREM. The final processed model facilitates the small-scale farming societies from Brazil to understand and cultivate crops with higher adaptivity to a particular region. This positively influences the growth and yield, solves the problems that have adverse effects on the economic status of farmers, and also aids in developing ecosystem-friendly agricultural approaches (Sasso et al., 2021).

Agribot: AI-mediated Robotics for agricultural sustainability:

Mohan et al., 2023 studied the integration of several robotic systems for the purpose of agricultural development. The authors highlighted a real-time robotic weed knife control system for crops like lettuce and tomato, a laser weeding prototype robot. Both systems provide a solution that counters the costly traditional hand-oriented weed removal systems and checks the utilization of chemical inputs, thus benefiting pollution control and facilitating sustainability. They utilize computer vision and machine learning technologies to detect and eliminate the target weeds without causing any harm to the crops.

Limitations:

High cost is a serious concern that limits farmers' implementation of smart technologies. Threads related to privacy, i.e., confidentiality of the farmer’s data, are also a serious concern to deal with (Jose et al., 2021). The requirement of high computational power for the functioning of AI, in turn, leads to increasing the extent of global warming (Singh and Kaur., 2022). Another problem is the doubt of farmers about the abilities of AI to solve real-life problems. According to them, a man can have a better understanding of the problems as compared to machines. They find it difficult to understand the processing related to AI, and the expense of these high-tech devices shifts their attention only toward the problems and overshadows the positive impacts of AI (Mohan et al., 2023). Lack of knowledge of the rural farmers about the existence of such intellectual, smart agricultural methods is also a big hindrance in the way of developing AI-based agricultural methods (Javaid et al., 2023).

Conclusion:

In summary, it is clear that urgent action is needed to address the detrimental impacts of modern agricultural practices on ecosystems and human well-being. The dependency on chemical inputs and high-tech machinery, driven by the escalating demands of a growing population, has led to the neglect of sustainability. However, integrating artificial intelligence (AI) offers a transformative solution. AI facilitates early prediction of pests, diseases, and environmental conditions, optimizing resource utilization while minimizing the reliance on harmful chemicals. Smart agricultural approaches powered by AI enable precision farming and efficient resource management. Furthermore, AI-driven agroecological principles offer sustainable solutions by leveraging traditional knowledge with modern technology. Despite challenges like cost and farmer hesitation, the transformative potential of AI in advancing agricultural sustainability cannot be overlooked. Efforts to overcome limitations and promote awareness among farmers are essential for realizing the full benefits of AI in agriculture.

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HOW TO CITE

Mayuri Bhagawati*, Chayan Dhar, Dipan Sarma, Manna Das, Badal Kumar Datta (2024). Integration of artificial intelligence toward better agricultural sustainability. © International Academic Publishing House (IAPH), Dr. Suman Adhikari, Dr. Manik Bhattacharya and Dr. Ankan Sinha, *A Basic Handbook of Science, Technology and Innovation for Inclusive Development [Volume: 1]*, pp. 71-85. ISBN: 978-81-969828-4-3.

DOI: https://doi.org/10.52756/ bhstiid.2024.e01.005