Artificial Intelligence and Data Science for Sustainable Agriculture: A Comprehensive Analysis of Technologies, Applications, and Implementation Challenges

Rohit Kumar[1], Aditya Kalra[2], Akshay Kumar[3], Piyush Sewal[4]

rohitkumar71515@gmail.com[1], aditya.kalra.cs@gmail.com[2], akshupandit0808@gmail.com[3], piyush.sewal@gmail.com[4]

Yogananda School of AI, Computers and Data Sciences Shoolini University Solan, India [1,2,3]

Amity School of Engineering and Technology, Amity University, Punjab, India [4]

Abstract: The transformative potential of Artificial Intelligence (AI) and Data Science (DS) in modern agriculture is increasingly recognized as a solution to global challenges of food security, resource optimization, and sustainable farming. This paper presents a comprehensive analysis of AI and Data Science technologies such as Fuzzy Logic, Artificial Neural Networks (ANN), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Artificial Potential Field (APF), Simulated Annealing (SA), and data-driven predictive models applied in agriculture. The study highlights how AI–Data Science integration empowers precision and smart agriculture through innovations like automated irrigation, crop yield prediction, pest and disease detection, autonomous farm equipment, and data-enabled supply chain optimization. It further explores how these technologies enhance productivity and sustainability while minimizing environmental impact. The paper identifies key implementation challenges—including data quality, model interpretability, and adoption barriers—and recommends future research in explainable AI, hybrid intelligent systems, and climate-adaptive solutions. This review underscores the synergistic role of AI and Data Science in driving the next generation of sustainable agricultural innovation and serves as a valuable resource for researchers and practitioners aiming to advance smart and resilient farming systems.

Keywords: Artificial Intelligence, Precision Agriculture, Sustainable Farming, Crop Yield Prediction, Autonomous Farm Equipment, Explainable AI

1 Introduction

As the world becomes increasingly populated, the agricultural sector is confronted with simultaneous resource and climate change challenges that inhibit the sustainability of agriculture. The agricultural sector has been traditionally reliant on human labor and experience. While this may be sufficient to maintain human existence, it is generally incapable of optimizing productivity, resource efficiency, and sustainability in agriculture during these unprecedented times. In this context, AI has become a disruptor by shifting agriculture from subjective, manual, and empirical approaches to data-based, highly automated, and artificial

IICTDS 2025, December 19-20, Chandigarh, India
Copyright © 2026 EAI
DOI 10.4108/eai.19-12-2025.2366185

intelligent-algorithm (AI) operational methods, as presented in Fig. 1 [1]-[3]. Smart agriculture intends to utilize AI for not only obtaining enhanced crop yield, minimizing waste, and supporting sustainable agriculture through precision farming, predictive analytics, and autonomous systems [4]-[6]. The aim of this paper is to describe the significant and rapid impacts that AI technologies are having on the agriculture sector from new technologies to cutting-edge applications.

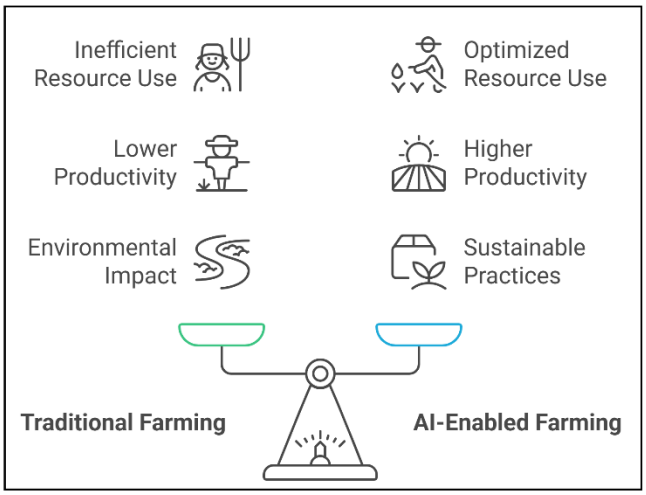


Fig. 1: Traditional Farming vs AI_Enabled Farming

Contemporary agriculture employing AI relies on high-performance computing frameworks to ingest and analyze huge amounts of complex agricultural data efficiently. Distributed platforms such as Apache Spark and Hadoop and distributed storage systems allow for data at such a scale to be processed and ingested, something not seen in traditional agriculture [7], [9]. Farmers have real-time access to consider, process, and analyze variables such as soil health, climate and weather patterns, as well as crop conditions. Therefore farmers now have actionable items, such as precision irrigation, optimized fertilizer application, and logs of crop health were some improvements in resource performance. Similarly, AI systems connected with the Internet of Things and remote sensors significantly improve productivity while reducing impact on the environment. Together these innovations are a model of smart agriculture with defined interdependences linking all aspects of furthest part of the production system back to the restoration of soil health through Faith and Regeneration.

This paper delivers a holistic overview on important techniques of Artificial Intelligence, such as Fuzzy Logic, Artificial Neural networks (ANN), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Artificial Potential Field (APF) and Simulated Annealing (SA), and their application in agriculture. We examined studies previously published and summarized them in a tabular form to show trends, advantages and disadvantages of the research studies for each approach. The study also pointed out main gaps in the current implementations of AI and future consideration, such as the implementation of explainable AI models, hybrid optimization techniques, climate-adaptive solutions, etc. The goal of this research is to close

the gap between state of the art theoretical advances in the field and application in practice to help direct researchers, agronomists and policy makers to utilize AI techniques towards more sustainable and productive agricultural systems

2 AI Techniques used in Agriculture

Artificial intelligence (AI) is changing modern agricultural practice (also known as precision, or smart farming) via sophisticated applications of fuzzy logic to handle uncertainty, artificial neural networks to recognize patterns and predict yield, genetic algorithms to improve crop breeding processes, particle swarm optimization to manage inputs efficiently, and artificial potential fields for navigation of autonomous farming machinery. These AI techniques are modernizing traditional farming practices into precision agriculture systems that can make timely and data-driven decisions to promote efficiency and sustainability. An overview of these techniques have been presented in Fig. 2.

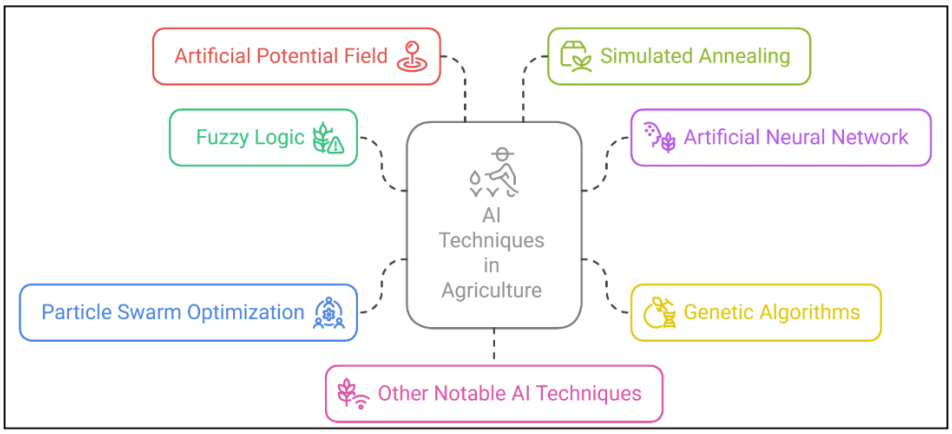


Fig 2: AI Techniques used in Agriculture

2.1 Fuzzy Logic

Fuzzy logic is commonly adapted in agriculture to handle imprecise and uncertain data, making it ideally suited for decision making in an environment subject to varying conditions. Fuzzy logic systems have been specifically used in irrigation control systems for this reason. For example, soil moisture, weather predictions and crop demands all vary based on measurable and unmeasurable variables, thus uncertainty occurs. Implementing fuzzy logic-based controllers in watering schedule optimization enables farmers to provide the best schedules without over or under-watering their crops. Fuzzy logic systems are also helpful in predicting pests and diseases through analyzing vague symptoms and environmental factors that could lead to the creation of issues down the road. [11], [14].

Another prominent application of fuzzy logic is through climate control in greenhouses, which would require the management of temperature, humidity, and CO_2. The relationship between these environmental factors is extremely nonlinear thus rendering a traditional control system unfeasible and incapable of adaptive management. A fuzzy logic based controller would enable the farmer to manage these aspects holistically and improve crop growth by creating optimal conditions for the crop to grow. Similar to using fuzzy logic in climate control in this scenario, fuzzy systems are utilized in yield prediction models by blending the best known expert knowledge of the crop type with sensor data to create yield predictions that are more accurate than a typical statistical yield prediction model or method [5].

2.2 Artificial Neural Network

Artificial Neural Networks (ANNs) are integral to agriculture since they can automatically identify complex patterns within big data. One of the most prevalent applications of ANNs is crop yield prediction. Typically, crop yield prediction involves ANNs analyzing historical weather events, soil quality, and how farmers treat fields to predict crop production levels adequately [4]. ANNs also expand beyond crop yield prediction by assisting farmers with precision agriculture. For instance, ANNs monitor crop health in real-time using drone or satellite imagery and can spot nutrient deficiencies, water stress, and disease outbreaks before they become problematic.

In terms of livestock management, ANNs serve as a tool for analyzing animal behavior, feed efficiency, and general animal health, to improve breeding and prevent disease. ANNs are also applied to post-harvest considerations. For example, ANNs will assist in quality sorting of fruits and vegetables using computer vision to classify produce based on size, colour, and defects. ANNs will also assist with newer deep learning models that are learning how to navigate autonomous farming machinery, allowing self-driving tractors and harvesters to travel through the field while avoiding obstacles [14, [17].

2.3 Genetic Algorithms

Genetic Algorithms (GAs) are optimization strategies that are modeled after natural selection, enabling them to be especially helpful in the solution of complex agricultural problems. One of the most common applications is in crop breeding. Use of GAs allows researchers to identify some of the best genetic combinations for developing broad acre plant varieties that are high-yield, disease-resistant, and more resilient to climate change. Simulating the evolution process allows researchers to reduce selection time in breeding to minutes as opposed to the weeks or months typically elapsed using traditional approaches [18].

GAs are also used as a resource allocation tool, for example determining the best planting schedule, most effective fertilizer application and best irrigation plans, all geared toward achieving the most you can from available inputs. In the case of farm machinery routing, GAs help plan the shortest path of autonomous enabled farm machinery on a predetermined track to minimize fuel consumption and avoid overlap of fields. GAs also used to enhance supply chains, to ensure that harvested produce with the least possible waste and cost is delivered to market [19].

2.4 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a computational process used to optimize agricultural systems using a model of group behavior found in swarms. One use of PSO is precision irrigation. The PSO algorithm can determine how much and where to distribute water across a field based on data from soil sensors and weather forecasts. This reduces water waste, ruining crops due to under or over application of moisture. PSO can also be applied to determine pest management strategies, such as application of traps and pesticides. This will minimize the amount of pesticide used without lowering effectiveness [17].

Another key use of PSO is optimizing agricultural machines by automating them. For example, PSO could help carry out autonomous routings for tractors and other implements that reduce energy consumption and soil disturbance. PSO can also help automate climate control of a greenhouse by controlling a dynamic heating, cooling, and ventilation systems so apertures are opened or closed to optimize plant growth. PSO can be beneficial as it permits calibration of each moving part for multi-objective optimization and decision-making under multiple resource constraints or conflicting priorities, such as yield versus sustainable cropping systems [17].

2.5 Artificial potential field

Artificial Potential Fields (APFs) are useful in autonomous agricultural robot applications for navigation and obstacle avoidance (Dewey et al., 2019). Self-driving tractors and harvesters while they navigate through fields typically use an APF algorithm to move efficiently through fields while avoiding static obstacles (trees, rocks, etc.) and dynamic obstacles (animals, workers, etc.). This method creates virtual fields of forces to guide a machine along the best path, while increasing safety and efficiency [6].

In addition to navigation, APFs are used in precision spraying, where a drone or robotic sprayer alters its path through the field to target a weed or pest, while avoiding damage to crops. Resulting in less chemical usage and environmental contamination. APFs are also used in livestock management systems where autonomous herding robots are used to help navigate and guide livestock while minimizing stress, causing less disruption to livestock.

2.6 Simulated annealing

Simulated Annealing (SA), which has been inspired by the process of annealing in metallurgy, has shown to be a valuable optimization tool for agricultural processes and particularly, a rich area for application of the method for complex, non-linear problems. SA can simply be defined as a stochastic or probabilistic optimization method used to optimize a function/objective with a large search space. The search space is usually defined with respect to the physical and biological limits such as water availability and reasonable limits on growing degree days and soil fertility. One example of SA is optimizing irrigation schedules, using SA to arrive at a configuration for planting and farming in agriculture is especially valuable. SA has been used to assist with supply chain coordination to minimize food waste and reduce transportation costs through choosing the most favorable routes and conditions for transportation and storage of agricultural perishable goods [16].

The unique nature of SA, allowing an agent to escape a local optimum or maximum makes the exploratory tool useful for solving agricultural problems with multiple objectives (e.g., maximizing yield while minimizing chemical inputs, maximizing yield, and providing ecologically sustainable practice). It is widely regarded that hybrid methods produce better predictive models, thus incorporating SA with other Artificial Intelligence methods (genetic algorithms) greatly enhances prediction for modeling crop disease outbreaks and climate change adaptation methods. With increasingly available computing power, there is a great potential for SA to provide robust and reliable responses to resolve and explore large, dynamic problems within agriculture and farm/ranch management for sustainable farm management practices [18].

2.7 Other Notable AI Techniques in Agriculture

In addition to these approaches, artificial intelligence-based methods such as support vector machines (SVM) for disease classification and decision trees for farm management recommendations, reinforcement learning for adaptive robotic farming applications, and computer vision for quality inspection are gaining popularity. Furthermore, blockchain combined with AI is focusing on providing supply chain transparency, and digital twins allow for digital farm simulations that can be used for predicting future events [23]. All of these technologies lead us toward more intelligent, sustainable farming practices.

An overview of AI techniques used in agriculture have been summarized in Table 1.

Table 1. AI Techniques used in Smar Agriculture

Category	Reference	Problem Statement	Proposed Solution	Limitations
Fuzzy Logic	[5]	Need to automate the classification of tomatoes based on colour, size, and hardness.	Developed a fuzzy logic-based system to classify tomatoes using a fuzzy membership function and Instron compression test	Limited to classification; no application to broader agricultural issues.
	[11]	Improve efficiency of agricultural robots through enhanced control systems.	Proposed fuzzy adaptive controllers to improve robot steering and autonomous navigation in agriculture.	Lacks real-world testing and scaling to larger agricultural operations
	[14]	High manual effort in harvesting crops.	Applied fuzzy logic to automate the harvesting process using robotic arms with vision-based feedback systems.	Limited to specific crops and lacks generalizability to other types of farming.
Artificial Neural Networks (ANN)	[14]	Difficulty in automating the harvesting of strawberries using machine vision.	Designed an ANN-based agriculture robot system to identify and harvest strawberries.	Limited to strawberry harvesting and requires further validation on other crops.

	[4]	Inability to predict flowering and maturity of soybean crops.	Applied ANN to predict flowering and maturity times using temperature, photoperiod, and other data inputs.	Requires larger datasets for better accuracy and generalizability across regions.
	[17]	Difficulty in accurately identifying and segmenting apples during the harvest phase.	Developed CNN-based apple recognition system optimized by genetic algorithms.	The system's performance decreases in challenging lighting or weather conditions
Genetic Algorithm (GA)	[18]	Difficulty in optimizing the motion planning of agriculture robots.	Applied genetic algorithms for path planning to reduce energy consumption and time in field operations	Lacks hybrid approaches with other AI techniques to further optimize path planning.
	[19]	High energy consumption in UAV-based trajectory planning in agricultural fields.	Optimized UAV trajectories using genetic algorithms, reducing energy usage and improving coverage.	Requires further optimization to handle more complex field environments and obstacles.
Particle Swarm Optimization (PSO)	[17]	Need for optimizing cotton picker robots in complex environments.	Applied PSO with K-means clustering to optimize performance in complex cotton fields.	Only tested in simulation; lacks real-world validation.
Artificial Potential Field (APF)	[6]	Difficulty in navigating autonomous agricultural robots through fields.	Used APF with sensors to guide robots, avoiding obstacles while performing tasks like crop monitoring and weed removal.	Works primarily in controlled environments; needs testing in more diverse field conditions.
Simulated Annealing (SA)	[16]	Inefficient water usage in irrigation systems.	Proposed an optimal irrigation scheduling system using SA, leading to more efficient water management.	Requires further integration with real-time environmental data to improve
	[18]	Inefficiencies in scheduling harvest activities in complex field environments.	Developed a hybrid SA-GA model to optimize scheduling during the harvesting phase, improving efficiency.	Needs more testing on different crop types and farming setups for generalization.

3 Notable Studies utilizing AI and Data Science in Agriculture

Traditional farming methods are mostly based on human expertise, which is prone to inefficiencies, inaccuracies, and the inability to scale with the growing demand for food and agricultural resources. The research has therefore addressed how integrating AI technologies can be a helpful tool to enhance productivity and decision-making.

An AI-based crop monitoring system utilizing drones and computer vision was introduced to detect crop health and predict yield. The system employed machine learning models trained on multispectral image data, collecting drone images from 15 farms and annotating them for health metrics such as leaf discoloration and pest infestation. A convolutional neural network (CNN) was trained to classify crop conditions, and the results showed that the proposed system achieved a 92% accuracy in identifying crop health, while the shortcomings included reliance on high-quality drone equipment, limiting accessibility for small-scale farmers. Similarly, to address supply chain inefficiencies caused by inaccurate yield predictions, a machine learning-based regression model was developed using historical yield data and weather patterns. Results indicated that the model reduced prediction errors by 15% compared to traditional statistical approaches; however, the shortcomings were evident as accuracy decreased under extreme weather conditions. To mitigate environmental concerns, an AI-powered pesticide optimization system using sensors and machine learning models determined the minimum effective pesticide application rates [18], resulting in a 50% reduction in pesticide usage, though limited by the dependency on expensive sensors.

Furthermore, AI technologies have been effectively applied to support farmers in adapting to modern agricultural practices. An AI-based training platform [19] employed adaptive learning algorithms to provide personalized training modules, where results revealed improved farmer technology adoption rates by 30%, though shortcomings included limited access in remote regions. Enhancing financial decision-making, an AI-based pricing model analyzed historical price data and demand patterns to recommend optimal selling prices. Results showed an 18% increase in farmer profits, but shortcomings arose from susceptibility to sudden market fluctuations. Addressing post-harvest losses, an AI-based storage monitoring system integrated IoT sensors and machine learning models to monitor temperature and humidity levels, achieving a 15% reduction in losses; however, its dependence on a consistent power supply remained a limitation.

AI and Data Science applications are also being leveraged to improve long-term agricultural resilience. A climate-resilient crop recommendation system using AI analyzed climate and soil data to identify optimal crop selections, leading to a 20% improvement in farmer income during pilot studies, though shortcomings included limited adaptability in regions with sparse climate data [2], [3]. For better water resource management, a smart irrigation system based on AI-driven weather predictions and soil moisture sensors analyzed real-time data to recommend optimal watering schedules, achieving up to 30% water savings compared to traditional methods, though the high implementation cost restricted adoption by small farms [4]. Additionally, an AI-powered disease detection system using image processing and deep learning trained a CNN on leaf images from 20 crop types, achieving 93% accuracy in disease identification. The main shortcoming, however, was reduced performance when tested on crop varieties outside the training dataset [6].

4 Limitations and Challenges of AI in Real-World Agricultural Applications

AI in agriculture also has various limitations which impair the efficiency of technology in the real world. One big question is the “black-box” nature of most AI models, making them harder

to interpret and hence losing trust in farmers and other agricultural stakeholders [24]. The gap between research and practical commercialization of a new finding is another huge concern especially in developing nations and thus few developers have been enthusiastic to embrace AI technologies [25]. The further problem of progress is legal and regulatory issues where the current policies may not be sufficient to cover the essential areas of data privacy, product and operational safety in AI-enabled farming [26]. Also, due to low income and high cost of implementation of AI solutions, smallholder farmers cannot easily afford it thus contributing to the widening of gaps in access to agricultural innovation [25], [27]. The combination of AI, IoT, and robotics has promised a lot, but there are still challenges: these systems are left without a sufficient level of operational efficiency, difficulties in establishing relations with other systems, and the problem of the shortage of specialists who should be entrusted with the supervision and maintenance of such complicated systems [28].

The variability and intricacies of agricultural environments also pose another important obstacle to testing, adaptation and validation of AI models. This is much more complicated in agricultural environments than in more controlled industrial environments [29]. Infrastructure restrictions and expense of computerized tools remain an impediment also, especially in under-staffed and outlying locating agricultural regions. High-quality context-aware data is a key success factor of AI applications, though the quality of context-aware data is frequently poor or lacking altogether, diminishing the reliability and scalability of models [30]. Ethical issues like data ownership, biasness in algorithms, and untraceability among others also require close governance to make sure that deployment of AI is fair and responsible [31]. Additionally, the implementation of AI with conventional processes of agricultural activities can require the undertaking of fundamental transformation in the organizational behavior and decision-making and these transitions can be challenging to embrace and apply by the usual farmers [27]. Lastly, the overall trends of global climatic problems, land degradation, and the necessity to provide sustainable food production intensifications are still putting pressure on the AI solutions that are not reaching the status of being fully adapted to the challenges and climate resilient [32]. Nevertheless, AI is an effective facilitator of smart agriculture; all these challenges can be overcome with inclusive design, well-developed infrastructure, and favourable policy frameworks [27], [30].

5 Future Aspects of AI and Data Science

Future advancements in artificial intelligence (AI) and Data Science hold immense potential to revolutionize agricultural practices further. The integration of cutting-edge technologies such as quantum computing, edge AI, and blockchain can enhance the efficiency, scalability, and security of AI systems in agriculture. For instance, quantum computing can process complex models more rapidly, enabling real-time decision-making for dynamic crop and pest management [20]. Edge AI, on the other hand, promises decentralized and faster data processing directly on agricultural devices, eliminating latency issues and reducing dependency on centralized infrastructure [5].

Additionally, the incorporation of explainable AI (XAI) into agricultural systems can bridge the gap between complex AI models and their practical implementation by ensuring transparency and fostering trust among farmers. Future research should also focus on the

development of robust AI systems capable of adapting to diverse climatic and geographical conditions, addressing the challenges of scalability. Moreover, efforts to create affordable and user-friendly AI tools can help small-scale farmers benefit from technological advancements, ensuring equitable growth across the sector [2], [3].

Collaborative approaches, including public-private partnerships and international collaborations, will be essential for funding and scaling AI research. Educational programs targeting digital literacy for farmers can further amplify the adoption of AI-driven solutions. Lastly, ensuring ethical AI practices, data privacy, and addressing socio-economic concerns should remain a priority to sustainably integrate AI into the agricultural domain [21].

6 Conclusion

The integration of Artificial Intelligence (AI) and Data Science (DS) in agriculture demonstrates immense potential to enhance efficiency, productivity, and sustainability through data-driven decision-making and intelligent automation. This paper has comprehensively analyzed key AI and Data Science techniques—including Fuzzy Logic, Artificial Neural Networks (ANN), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Artificial Potential Field (APF), and Simulated Annealing (SA) and their applications in precision irrigation, crop disease detection, autonomous equipment, and data-enabled supply chain optimization. The comparative analysis underscores the adaptability and transformative potential of these technologies in advancing sustainable and efficient farming systems.

Looking ahead, next-generation AI–Data Science integrations such as Edge AI with IoT, Explainable AI (XAI), and hybrid intelligent models will be crucial for achieving transparency, scalability, and inclusion. Emphasizing affordable and climate-resilient data models for smallholder farmers remains essential to ensure equitable technology adoption. By addressing these implementation challenges, AI and Data Science together can drive a sustainable, high-yield, and resilient agricultural future, bridging innovation and inclusivity in global food systems.

References

[1] Gupta, T., Sharma, A., Aryan, Rana, K., Sewal, P.: Utilizing Twitter data and NLP to analyze and predict public sentiment trends in mental health. *Proceedings of International Conference*, pp. 119–133 (2024)
[2] Eli-Chukwu, N. C.: Applications of artificial intelligence in agriculture: A review. *Engineering, Technology & Applied Science Research*, pp. 1–12 (2019)
[3] Liu, S. Y.: Artificial intelligence (AI) in agriculture. *IT Professional*, IEEE Computer Society, pp. 1–8 (2020)
[4] Shamshiri, R. R. et al.: Research and development in agricultural robotics: A perspective of digital farming. *International Journal of Agricultural and Biological Engineering*, vol. 11, no. 4, pp. 1–11 (2018)
[5] Javaid, M., Haleem, A., Khan, I. H., Suman, R.: Understanding the potential applications of artificial intelligence in agriculture sector. *Advanced Agrochem*, vol. 2, no. 1, pp. 15–30 (2023)
[6] Sarkar, U., Bannerjee, G., Das, S., Ghosh, I.: Artificial intelligence in agriculture: A literature survey. *International Journal of Scientific Research in Computer Science, Applications and Management Studies*, pp. 1–10 (2018)
[7] Sewal, P., Singh, H.: Analyzing distributed Spark MLlib regression algorithms for accuracy, execution efficiency and scalability using best subset selection approach. *Multimedia Tools and Applications*, vol. 83, no. 15, pp. 44047–44066 (2024)
[8] Sewal, P., Singh, H.: Algorithmic proficiency in Spark configuration tuning: An empirical study using execution time metrics across varied workloads. *Procedia Computer Science*, Elsevier, pp. 2307–2317 (2024)
[9] Sewal, P., Singh, H.: Analyzing distributed Spark MLlib regression algorithms for accuracy, execution efficiency and scalability using best subset selection approach. *Multimedia Tools and Applications*, vol. 83, no. 15, pp. 44047–44066 (2024)
[10] Sharma, S., Verma, K., Hardaha, P.: Implementation of artificial intelligence in agriculture. *Journal of Computational and Cognitive Engineering*, vol. 2, no. 2, pp. 155–162 (2023)
[11] Mckinion, J. M., Lemmon, H. E.: Expert systems for agriculture. *Artificial Intelligence Applications*, pp. 1–12 (1985)
[12] Shahjalal, M., Alam, M. Z., Miah, S. S., Chowdhury, A. H.: Fuzzy logic approach for identifying the effects of climate change on agricultural production. *International Journal of Agricultural Economics*, vol. 6, no. 4, pp. 181–190 (2021)
[13] Fujiwara, H.: Discriminating robot system for carnation seedling with fuzzy logic. *Proceedings of Agricultural Automation Conference*, pp. 1–8 (Year not specified)
[14] Jha, K., Doshi, A., Patel, P., Shah, M.: A comprehensive review on automation in agriculture using artificial intelligence. *Artificial Intelligence in Agriculture*, pp. 1–12 (2019)
[15] Morimoto, T., Hashimoto, Y.: An intelligent control technique based on fuzzy controls, neural networks and genetic algorithms for greenhouse automation. *Control Engineering in Agriculture*, pp. 1–15 (1998)
[16] Pasqual, G. M., Mansfield, J.: Development of a prototype expert system for identification and control of insect pests. Elsevier Science Publishers, pp. 1–12 (1988)
[17] Roach, J., Virkar, R., Drake, C., Weaver, M.: An expert system for helping apple growers. *Agricultural Expert Systems Symposium*, pp. 1–10 (1987)
[18] Mozny, M., Krejci, J., Kott, I.: CORAC hops protection management systems. *Agricultural Decision Support Systems*, pp. 1–10 (1993)
[19] Batchelor, W. D., McClendon, R. W., Adams, D. B., Jones, J. W.: Evaluation of SMARTSOY: An expert simulation system for insect pest management. *Agricultural Systems*, pp. 1–12 (1989)
[20] Thorpe, K. W., Ridgway, R. L., Webb, R. E.: A computerized data management and decision support system for gypsy moth management in suburban parks. *Decision Support Systems in Agriculture*, pp. 1–12 (1992)

[21] Batchelor, D., McClendon, R. W., Wetzstein, M. E.: Knowledge engineering approaches in developing expert simulation systems. *Expert Systems with Applications*, pp. 1–15 (1992)
[22] Vincent, D. R., Deepa, N., Elavarasan, D., Srinivasan, K., Chauhdary, S. H., Iwendi, C.: Sensors-driven AI-based agriculture recommendation model for assessing land suitability. *Sensors*, vol. 19, no. 17, pp. 1–18 (2019)
[23] Wakchaure, M., Patle, B. K., Mahindrakar, A. K.: Application of AI techniques and robotics in agriculture: A review. *Artificial Intelligence in Life Sciences*, vol. 3, pp. 1–12 (2023)