

Automation and AI in Precision Agriculture: Innovations for Enhanced Crop Management and Sustainability

ABSTRACT

This study offers an in-depth look at the most recent developments in artificial intelligence (AI) and automation in precision agriculture (PA), with a particular emphasis on important technologies such as like drones, autonomous tractors, AI-driven irrigation systems, and predictive analytics for crop management. The accuracy of crop monitoring and health assessments has increased by 30–50% per cent as a result of AI-powered solutions, which have improved resource-based decision-making. Systems for precision irrigation and fertilization have increased crop yields by 5–15% per cent while when using 25–40% per cent less water and 30–40% per cent less fertilizer, respectively. Robotic harvesters and sprayers are examples of automation technologies that have reduced labour expenses by 20–40% per cent and increased operational efficiency by 35% per cent. Additionally, AI-based prediction models have reduced pest damage by 20–25% per cent and reached an accuracy of 85–90% per cent for crop yield forecasts and pest control. Despite these developments, issues with of scalability, affordability for small farms, and data privacy still exist. The evaluation follows by outlining ideas for future research, such as 5G, blockchain, and AI integration with cloud and edge computing, to enhance decision-making and transparency.

Keywords: Precision agriculture, AI, Farm automation, Predictive analytics, Autonomous systems, Sustainable farming

1. INTRODUCTION

1.1 Background

A farming management strategy that considered precision agriculture (PA) uses makes use of modern technologies to monitor and control crop, field, and livestock variability [1]. This strategy improves sustainability, reduces its negative effects on the environment, and maximizes production efficiency. PA can identify different regions with varying necessities, enhancing yields, reducing waste, and saving expenses [2]. GPS, remote sensing, sensors, drones, and data analytics are just a few examples of the technologies that enable make site-specific management possible. These technologies enable farmers to identify and react to different situations within the same field. The growing global population makes PA an important domain for innovation and research [3].

1.2 Role of Automation and AI

Automation and artificial intelligence (AI) have significantly benefited agricultural techniques through higher productivity and precision. Automation in precision agriculture employs

autonomous machinery, including tractors, robotic harvesters, and drones, to lower labor demands and enhance operational efficiency [4]. AI improves automation through the analysis of extensive datasets, pattern recognition, and real-time decision-making. Machine learning algorithms can forecast crop health, enhance irrigation schedules, and identify pests at an early stage [5]. This transition from reactive to proactive agriculture allows farmers to enhance input efficiency, increase yields, and minimize environmental repercussions. These technologies facilitate sustainable agricultural practices and enhance food production, satisfying global food demand while addressing issues such as climate change and resource shortages.

1.3 Current Trends

Precision agriculture is experiencing growth owing to developments in automation, AI, and data analytics [6]. Autonomous tractors, sprayers, and harvesters are progressively employed for activities such as planting, spraying, and harvesting, whereas drones are utilized for crop health assessments and feedback applications. AI is employed to develop predictive models for agricultural yields, disease identification, and irrigation optimization. Machine learning algorithms analyze extensive data from sensors and meteorological predictions, yielding actionable insights. Internet of Things (IoT) devices assess environmental conditions and deliver real-time data for accurate management decisions [7]. Big data analytics are employed to examine trends and offer recommendations. Cloud computing enables the storage and processing of a substantial number of datasets. Blockchain technology is being investigated for food traceability and supply chain transparency, guaranteeing safe information regarding the origin, handling, and quality of agricultural products [8].

1.4 Scope and Objectives

This study investigates the use of automation and AI in precision agriculture, emphasizing their utilization to enhance crop yield, minimize resource waste, and support sustainable agricultural practices. It studies the advancement of autonomous machinery, robotics for agricultural operations, and the use of big data and AI in providing immediate feedback. The paper outlines the problems in the implementation of AI and automation in precision agriculture, alongside rising trends and research pathways. Also, the article critically examines the effects of automation and AI in agriculture, highlighting their potential impact on farming practices.

2. TECHNOLOGICAL LANDSCAPE IN PRECISION AGRICULTURE

2.1 Key Technologies

Precision agriculture employs advanced equipment for effective monitoring and administration of agricultural operations, facilitating data-driven decision-making and real-time interventions in modern agriculture. Sensors gather real-time data on crop and soil parameters, including soil moisture, temperature, humidity, nutrient levels, and plant health [9]. Common sensors include soil moisture sensors for irrigation optimization, temperature and humidity sensors for environmental monitoring, nutrient sensors for fertilizer application [10], and optical sensors for plant health evaluation. These data facilitates informed choices regarding irrigation, fertilization, and pesticide application, enhancing the accuracy of resource management. IoT has reshaped agriculture by connecting devices, sensors, and machinery across farms. These integrated systems relay real-time data to a central hub, allowing farmers to remotely oversee field conditions and automate processes, such as irrigation and fertilization. IoT-enabled smart irrigation enhances water efficiency and enables farmers to monitor factors such as livestock health and crop production via mobile applications or dashboards [9].

Drones, or unmanned aerial vehicles (UAVs), are employed in agriculture for aerial imaging, field mapping, and crop inspection [11]. Utilizing multispectral and infrared cameras, they deliver high-resolution images for assessing crop health, water stress, and pest infestations and facilitate precision application of fertilizers, herbicides, and pesticides [12]. GPS technology enhances precision agriculture by delivering accurate positioning data for field mapping and zoning, facilitating autonomous navigation for tractors and machinery, and enabling Variable Rate Technology (VRT) for input applications tailored to specific field conditions, thereby optimizing resource utilization and minimizing overlaps and gaps in agricultural operations. Robots are increasingly being used for agricultural tasks such as planting, weeding, harvesting, and spraying [13]. They can execute repetitive operations autonomously, utilize AI-driven algorithms for plant health evaluations, and function well under challenging conditions. For instance, robotic harvesters employ AI vision to select mature fruits and vegetables, whereas robotic weeders differentiate between crops and weeds [14].

2.2 AI and Machine Learning Applications

AI and machine learning (ML) are used in agriculture through real-time data analysis, predictive modeling, and decision-making support systems. These technologies facilitate predictive analytics, plant health assessment, precision irrigation, crop genomics, autonomous agricultural machinery, and yield enhancements. AI systems evaluate extensive datasets from sensors, drones, and meteorological stations to predict agricultural yields, pest and disease occurrences, and soil health [15]. Machine learning models can identify patterns, enabling farmers to implement preventive measures. AI-driven systems assess crop health, identify early indicators of illnesses, nutrient deficits, or water stress, and suggest suitable remedies [16]. Machine learning algorithms propose ideal irrigation schedules for nutrient application, enhancing yield and minimizing environmental impact. AI-operated autonomous tractors, drones, and harvesters function with minimal human oversight, adapting their operations according to real-time field circumstances. AI-driven decision support systems assist farmers in making informed choices, thereby minimizing input expenses and optimizing profitability.

2.3 Automation Tools for Field Operations

GPS-guided planting methods enhance seed utilization and crop establishment by eliminating overlaps and gaps [17]. Precision irrigation systems provide water according to real-time soil moisture data, thereby reducing water waste and preventing over-irrigation. Variable Rate Technology (VRT) facilitates the automated application of fertilizers and pesticides using spatial data, thereby minimizing chemical runoff and promoting environmental sustainability [18]. Robotic weeders employ computer vision and AI to differentiate between crops and weeds, thereby minimizing manual weeding and excessive herbicide application [19]. Automated harvesters, utilizing AI and machine vision, identify the optimal time for agricultural harvesting and execute the work with efficiency and accuracy [20]. Figure 1 illustrates the integration of several technologies inside the within a precision agricultural framework. These technologies result in enhanced productivity, cost efficiency, and sustainability in precision agriculture.

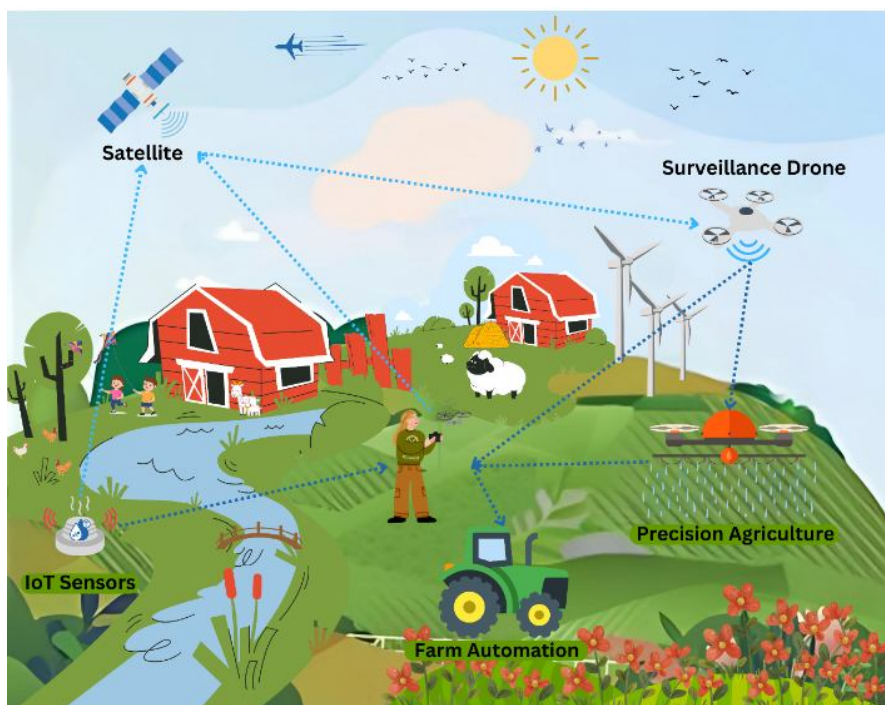


Fig.1. Smart technologies used in precision agriculture

3. AI-DRIVEN AUTOMATION IN CROP MANAGEMENT

AI helps crop management by facilitating automated, data-driven solutions for monitoring, decision-making, and ~~the~~ optimization of agricultural operations. The capacity of AI to analyze extensive datasets, identify patterns, and generate forecasts with remarkable accuracy improves the precision and efficiency of agricultural operations.

3.1 Role of AI

AI-driven systems utilize data from sensors, drones, and satellite imaging to identify early indicators of plant stress, like water deficiency, nutritional shortages, illnesses, or pest infestations. AI models analyze these photos to detect plant health problems, ~~facilitating~~ prompt actions and ~~minimizing~~ the risk of production loss [21]. Machine learning models based on extensive datasets of crop photos can ~~help~~ facilitate disease identification. AI systems consistently assess crop conditions, ~~offering~~ farmers relevant information, and ~~diminishing~~ human field inspections, ~~thereby hence-reducing cutting~~ labour costs and facilitating proactive crop management.

3.2 AI in Predictive Analytics

AI serves as a potent instrument in predictive analytics, assisting farmers in making ~~educated-informed~~ decisions by anticipating crop yields, meteorological conditions, and pest infestations. AI models evaluate previous data ~~on regarding~~ meteorological conditions, soil quality, cultivation methods, and crop survival to forecast future yields. AI-driven yield prediction technologies maximize resource allocation by integrating real-time data from field

sensors and drones [22]. Advanced machine-learning algorithms, including regression models, decision trees, and neural networks, forecast crop yields by associating environmental variables with previous data. AI models predict pest and disease outbreaks by examining environmental factors, crop data, and pest behavioural patterns [23]. These models offer early alerts and suggest precautionary [measuresactions](#). AI improves weather forecasting by incorporating hyperlocal data from sensors and satellites, resulting in more precise predictions of meteorological occurrences that affect irrigation plans, planting periods, and pest-control techniques.

3.3 Automated Systems

AI-driven automation improves precision in irrigation, fertilization, and pesticide application by optimizing resource use and minimizing waste [24],[25]. These systems use data from sensors, drones, and satellites, combined with AI algorithms, to deliver inputs precisely when and where needed. AI-based irrigation systems analyze real-time soil moisture data, weather forecasts, and crop requirements to determine [anthe](#) optimal irrigation schedule. AI-powered drip irrigation systems monitor soil moisture levels, [and](#) adjust water flow, [conserving](#) water, and [improving](#) plant health. AI-powered fertilization systems use Variable Rate Technology (VRT) to adjust fertilizer application based on soil fertility, [preventing](#) over-application and [reducing](#) environmental impact [26]. AI-optimized fertilization models recommend [anthe](#) ideal nutrient mix and timing for fertilizer applications, ensuring optimal nutrient availability and reduced runoff. AI-driven pesticide application uses vision systems mounted on drones or autonomous sprayers to identify pest-infested areas, [thereby](#) reducing chemical use, environmental damage, and input costs. The food processing sector [relies](#) significantly [relies](#) on automation and AI to enhance post-harvesting efficiency and increase output [27].

3.4 AI in Soil Health Monitoring and Nutrient Management

AI systems are employed to assess soil health and regulate nutrient levels, ensuring [that](#) crops have [the](#) appropriate nutrients at the optimal [timemoment](#). These systems incorporate soil sensors, drones, and data analytics to generate comprehensive maps of soil nutrient concentrations, [thereby](#) facilitating [VRThe](#) applications of VRT. Real-time soil data analysis enables AI models to suggest modifications to fertilizer application rates, enhancing crop nutrition and minimizing environmental impact [28]. AI models enhance nutrient management techniques by utilizing past crop data and soil analysis, advising on the most effective fertilizer types, application rates, and timing to improve nutrient absorption and reduce waste. Machine learning systems forecast vitamin deficits prior to their manifestation, [thereby](#) facilitating timely intervention. AI-driven systems assess soil composition, organic content, and microbial activity, [and](#) offering an extensive evaluation of soil vitality [29]. AI for sustainable soil management can forecast the long-term effects of agricultural operations, providing guidance on crop rotation, cover crops, and organic amendments. **Figure 2**[exemplifiesillustrates](#) the interrelation between AI, sensors, and automated systems.

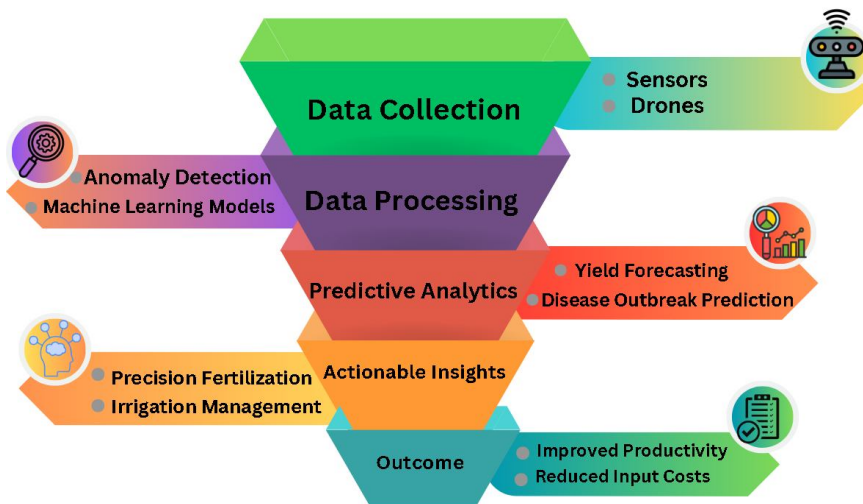


Fig.2. Schematic of AI-driven methodology for crop monitoring

4. ROBOTIC SYSTEMS IN PRECISION AGRICULTURE

Robotic systems in precision agriculture contribute to efficiency, production, and sustainability by automating [the](#) processes from planting to harvesting [30]. Crucial robotic technologies are being developed for their impact on [the](#) industry.

4.1 Autonomous Tractors and Robotic Sprayers

Autonomous tractors and robotic sprayers contribute to agricultural automation by mechanizing processes, such as plowing, planting, and tilling. These tractors employ GPS, sensors, and AI systems to enhance field operations, minimizing overlap and increasing fuel and time efficiency [4]. They enhance productivity by functioning constantly without interruptions, decreasing personnel expenses, and facilitating accuracy in operations, such as planting and fertilizer. Robotic sprayers utilize real-time data to modify administration volumes and locations, guaranteeing that chemicals are administered only where necessary. They can utilize sophisticated AI algorithms to identify canopy regions and modify the nozzle's orientation, thereby minimizing waste and enhancing chemical application efficiency [31].

4.2 Harvesting Robots

AI-driven robotic harvesting devices can recognize mature fruits by analyzing colour, size, and shape, and use machine learning algorithms to direct their arms for accurate harvesting. The robots are engineered for many crops, ranging from soft fruits such as strawberries and tomatoes to firmer vegetables like such as cucumbers and peppers. They modify their harvesting methods according to the distinct needs of each crop. This automation minimizes [the](#) dependence on manual labour and enhances speed and precision, guaranteeing optimal freshness and productivity.

4.3 Drones and UAVs

UAVs help [in](#) aerial assessments of crop health, facilitating planting, and executing precise spraying operations. Drones, outfitted with high-resolution cameras and multispectral

sensors, may can survey broad agricultural regions and, obtaining precise images of crop health [32]. They indicate regions of stress, illness, or nutritional inadequacy, enabling farmers to make informed decisions for prompt interventions. AI algorithms analyze these data to provide insights into plant health, allowing farmers to modify irrigation, fertilizer application, or pest control strategies according to real-time field circumstances. Drones are automating the planting process by depositing seeds straightdirectly into the soil, thereby minimizing manual labour and accelerating the procedure [33]. They are commonly used for the application of fertilizers and pesticides on crops, and providing flexibility in agricultural management. **Figure 3** highlights the various roles of robotics in automating farming tasks.



Fig. 3. AI-powered robotic systems

5. DATA-DRIVEN DECISION MAKING IN FARM MANAGEMENT

In order to maximize farm management choices and resource utilization, this section addresses the importance of data collection, AI-based data analysis, and the application of big data and AI in contemporary precision agriculture.

5.1 Importance of Data Collection

Precision agriculture depends on sensors integrated into the field or connected to agricultural devices to assess parameters, such as soil moisture, fertilizer concentrations, temperature, and crop health [34]. These sensors supply real-time data that can assist farmers in interpreting microclimates and implementing remedial actions to improve plant development and production. Drones outfitted with high-resolution cameras and multispectral sensors have transformed crop scouting and field monitoring by offering an aerial perspective of the farm [35]. These technologies facilitate the identification of crop diseases and nutritional deficits, allowing for timely treatments and reducing crop loss. Remote sensing technologies, such as satellite photography, provide extensive insights into soil conditions, crop health, and environmental factors, merging these with ground sensor data for a complete view.

5.2 AI-Based Data Analysis

AI serves as a potent instrument for the analysis of large and complex information derived from sensors, drones, and satellites. It employs machine-learning algorithms to forecast trends and produce recommendations, allowing farmers to make informed decisions in real-time. AI systems can forecast the optimal timings for irrigation, fertilization, or pesticide application by analyzing meteorological predictions and crop health information [36]. They assist farmers in making accurate judgments regarding resource allocation, avoiding waste, saving reducing costs, and promoting sustainability. AI can interact with automated agricultural machinery, ensuring precision in planting, irrigation, and input applications, thereby hence enhancing efficiency and minimizing labour and resource wastage [37].

5.3 Precision in Resource Management

AI-driven precision irrigation systems enhance water efficiency by calculating the precise water requirements for various areas [38]. These systems utilize real-time data on regarding meteorological conditions, soil moisture levels, and crop irrigation requirements to reduce water waste. They modify irrigation schedules according to soil moisture measurements and meteorological predictions, thereby enhancing water utilization efficiency. AI tools assist in arid regions by forecasting water requirements and offering strategies for water conservation [39]. AI-driven systems evaluate soil nutrient data to prescribe the appropriate quantity and type of fertilizer, minimizing waste and averting over-application. VRA systems provide fertilizers at varying rates throughout the field, minimizing expenses and ecological consequences. AI enhances energy efficiency in agricultural machinery and irrigation systems by timing activities for low-energy demand periods and regulating power output. It can also use renewable energy sources to enhance sustainable agricultural practices.

5.4 Use of Big Data and AI for Predictive Modeling

AI and big data technologies utilize historical data, meteorological patterns, edaphic conditions, and agronomic health parameters to predict future yields and suggest treatments to optimize production [40]. These models also detect dangers, such as drought, pest infestations, or disease outbreaks, offering early warnings and enabling farmers to implement preventive measures. AI algorithms can forecast pest infestations and disease outbreaks by evaluating real-time data, facilitating timely interventions, and minimizing crop damage. AI systems can enhance resource utilization by detecting trends in large data sets, enabling farmers to make informed decisions about resource allocation and management [41]. This facilitates the optimal utilization of inputs, including water, fertilizer, and energy, ensuring resource efficiency and sustainability. Utilizing AI, farmers may can make informed decisions that enhance resource efficiency, increase yields, and foster environmental sustainability. Figure 4 illustrates visualizes the importance of data-driven decision-making in precision agriculture.

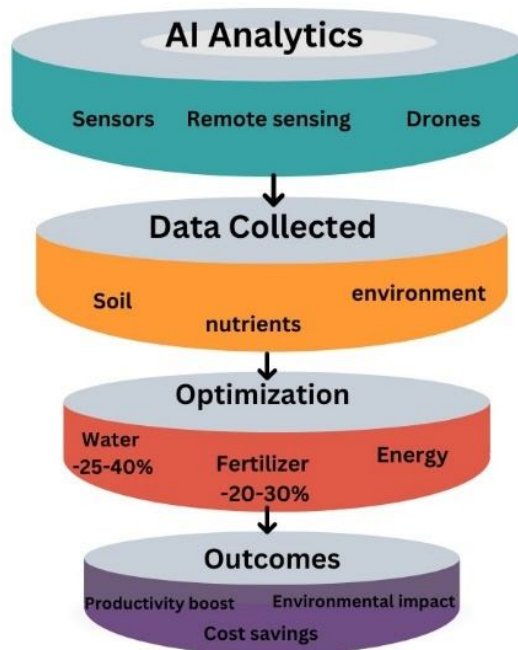


Fig.4. Data flow for decision-making

6. CHALLENGES AND LIMITATIONS IN IMPLEMENTING AI AND AUTOMATION

The technical, financial, data-related, and environmental obstacles that precision agriculture integration faces prevent it from being widely adopted, particularly in small and medium-sized farms.

6.1 Technical Challenges

Precision agriculture has technical obstacles that include [compatibility](#) among systems and technologies, scalability of AI solutions, and [the](#) precision and dependability of sensors [42]. The use of proprietary communication protocols by many suppliers makes it difficult to combine sensors, machines, drones, and AI-driven software. Expanding AI solutions to [huge](#) large farms or varied agricultural environments necessitates substantial infrastructure enhancements, including additional sensors, enhanced data storage capabilities, and superior internet connectivity [43]. The precision of [the](#) sensors is essential for reliable suggestions and agricultural management, necessitating constant calibration and maintenance [44]. [However](#) Still, continuous exposure to environmental elements, such as weather, dust, and vermin, can deteriorate sensors over time, necessitating replacements or regular repairs. Certain sensors may exhibit inferior performance [under](#) in extreme climatic [conditions](#) circumstances, presenting issues in areas with severe climates.

6.2 Economic Challenges

Automation technologies, including AI-driven systems, drones, autonomous tractors, and sensors, can impose significant financial burdens on small- and medium-sized farms [owing](#) due to their substantial initial investment requirements [45],[46]. These systems [require](#) necessitate routine maintenance and repairs, and equipment malfunctions

~~may~~ might result in expensive delays. The return on investment (ROI) from automation may not be instantaneous, particularly for small-scale agricultural operations. The unpredictability of forecasting ROI resulting from agricultural yields and variable crop prices dissuades small farms from investing in this technology [47]. Governments and agricultural organizations provide subsidies or financial assistance to facilitate farmers' use of automation; ~~still~~ however, these initiatives frequently lack sufficient reach and accessibility.

6.3 Data-Related Challenges

Concerns regarding data privacy and security ~~have~~ emerged, as agricultural operations increasingly depend on data-driven technologies. Precision agricultural technologies accumulate comprehensive information regarding farm operations, crop health, and resource utilization, rendering the misuse of sensitive information a significant risk [48]. Agricultural producers may lack clarity over the ownership of data produced by AI and automation technologies, while the digitization of agriculture stimulates susceptibility to hackers. Data management is a barrier, as some farms lack the requisite capacity to process substantial datasets. Cloud computing and edge computing are frequently necessary; nonetheless, they imply supplementary expenses and technical prerequisites [49].

6.4 Environmental Concerns and Sustainability Aspects

Automation technologies, like AI, can enhance resource efficiency while also affecting the environment [50]. They utilize energy for operation, contributing to the ~~carbon impact of farm's~~ carbon impact. This may provide challenges if the energy is derived from non-renewable sources, compromising the sustainability advantages of precision agriculture. The disposal of obsolete systems and gadgets presents environmental concerns, particularly in rural regions. AI may contribute to excessive land and soil utilization, necessitating a balance between ~~the~~ production and ~~the~~ long-term health of soil and biodiversity [51]. To reduce this, it is imperative to incorporate renewable energy sources such as solar-powered sensors and vehicles.

7. FUTURE TRENDS AND RESEARCH DIRECTIONS

Advanced technologies like AI, robotics, cloud computing, and blockchain will have an impact on the future of precision agriculture by enabling more intelligent, effective, and sustainable farming operations. Principal trends and research trends will influence this generation.

7.1 Integration of AI and Robotics in Farm Automation

The combined efforts of AI and robotics ~~is~~ are anticipated to propel substantial progress in agricultural automation, allowing robots to execute difficult jobs with no human involvement [52]. Fully autonomous farms, wherein AI-driven robots oversee all ~~the~~ phases of food production, represent an expanding field of research. Future robotic systems will probably incorporate many machines ~~collaborating~~, including drones and ground robots, to enhance overall agricultural operations [53]. AI-augmented harvesting robots ~~could~~ can manage various crop varieties with better accuracy and efficiency, minimizing crop waste and augmenting yields. Advanced sensors and AI-driven vision systems will add to robotic capabilities, facilitating precise manipulations ~~so~~ for individual plants [54].

7.2 Role of Cloud Computing, Edge Computing, 3-D Printing, and 5G

The integration of cloud and edge computing in precision agriculture will improve data processing and decision-making capabilities. Cloud computing facilitates real-time analysis of agricultural conditions, meteorological patterns, and resource requirements, empowering farmers to make data-driven decisions on a substantial scale [55]. Edge computing, by processing data ~~nearer~~ closer to the farm, diminishes latency and enhances response times

for immediate decision-making. 5G connectivity ~~will~~ facilitates uninterrupted interconnectivity among devices on ~~at~~ the farm, allowing for real-time oversight and management of machinery and systems [56]. This will enhance intervention precision, minimize resource wastage, and augment crop yields. 5G will facilitate the proliferation of ~~the~~ IoT in agriculture, enabling enhanced data collection and precision in farm management [57]. 3D printing technology significantly contributes to the production of tailored equipment and tools for farmers, hence enhancing ~~the~~ efficiency and productivity ~~of~~ in agriculture [58], [59].

7.3 Future of AI in Crop Genomics and Precision Breeding

AI ~~is~~ has been poised to transform crop genomics by ~~pinpointing~~ identifying genetic features that enhance production, disease resistance, and climate adaptability [60]. AI-driven algorithms may evaluate extensive genetic data to determine optimal features for breeding programs, expediting the creation of crops with favourable attributes such as drought resistance or pest tolerance. Precision breeding will facilitate the development of novel crop varieties with improved nutritional quality and environmental resilience [61]. Future AI systems will facilitate extensive agricultural phenotyping, allowing precise forecasts ~~ing~~ of crop performance across many settings.

7.4 AI-Driven Decision Support Systems

~~The~~ AI-driven DSS will evaluate data regarding meteorological conditions, soil vitality, crop development, and resource consumption, enabling farmers to enhance the utilization of water, fertilizers, and pesticides [62]. These systems will integrate climate models to assist farmers in adapting to evolving weather patterns, ~~and~~ providing guidance on planting dates, crop rotations, and watering schedules. AI ~~will~~ facilitates carbon farming methodologies, monitors carbon sequestration rates, and allow farmers to engage in carbon credit markets [63]. AI and blockchain technology will significantly contribute to transparent supply chain management, demand forecasting, minimizing food waste, and enhancing logistics. An AI-driven support system will enhance the optimization of solar-based aquaponic systems [64] and facilitate water recycling and purification technologies, such as membrane processes [65].

7.5 Blockchain for Transparency and Traceability

Blockchain technology, combined with AI, will improve transparency and traceability in agricultural supply networks [66]. It ~~will~~ documents the complete path of a product from farm to consumer, offering consumers ~~with~~ comprehensive information regarding its origin, agricultural methods, and certifications. This ~~will~~ guarantees that premium, sustainably cultivated products are delivered to consumers. AI ~~will~~ monitors and authenticates every phase of the supply chain, whereas blockchain offers an immutable record, mitigating fraud and guaranteeing product authenticity [67]. Investigations in these domains will influence the future of agriculture, benefiting farms of various levels.

8. CONCLUSION

The incorporation of AI with automation technology has substantially enhanced the efficiency, sustainability, and production of precision agriculture. AI-driven solutions have boosted agricultural monitoring and decision-making processes by 30–50% ~~per cent~~, leading to a reduction in water and pesticide usage by up to 30% ~~per cent~~. Automated machinery, including robotic tractors and sprayers, decreased labour expenses by 20–40% ~~per cent~~ and enhanced operational efficiency by as much as 35% ~~per cent~~. AI-driven predictive analytics technologies have empowered farmers to predict agricultural yields and foresee pest infestations with 85-90% ~~per cent~~ accuracy, resulting in improved resource allocation. The combined use of AI with irrigation, fertilization, and pesticide application systems has

resulted in a 25per cent% reduction in fertilizer usage and a 20per cent% decrease in water consumption, fostering cost efficiency and environmental sustainability. The return on investment for these technologies is typically achieved within 2-3 years, especially in large-scale enterprises. The future of agriculture will be interlinked and data-centric, with innovations in 5G, cloud computing, and blockchain, facilitating the emergence of fully autonomous farms.

REFERENCES

- [1] M. Yin, R. Ma, H. Luo, J. Li, Q. Zhao, and M. Zhang, "Non-contact sensing technology enables precision livestock farming in smart farms," *Comput. Electron. Agric.*, vol. 212, p. 108171, Sep. 2023, doi: 10.1016/j.compag.2023.108171.
- [2] G. S. Hundal, C. M. Laux, D. Buckmaster, M. J. Sutton, and M. Langemeier, "Exploring Barriers to the Adoption of Internet of Things-Based Precision Agriculture Practices," *Agriculture*, vol. 13, no. 1, p. 163, Jan. 2023, doi: 10.3390/agriculture13010163.
- [3] V. C. S.S., A. H. S., and G. F. Albaaji, "Precision farming for sustainability: An agricultural intelligence model," *Comput. Electron. Agric.*, vol. 226, p. 109386, Nov. 2024, doi: 10.1016/j.compag.2024.109386.
- [4] M. Padhiary, L. N. Sethi, and A. Kumar, "Enhancing Hill Farming Efficiency Using Unmanned Agricultural Vehicles: A Comprehensive Review," *Trans. Indian Natl. Acad. Eng.*, vol. 9, no. 2, pp. 253–268, Feb. 2024, doi: 10.1007/s41403-024-00458-7.
- [5] S. K. S. Durai and M. D. Shamili, "Smart farming using Machine Learning and Deep Learning techniques," *Decis. Anal. J.*, vol. 3, p. 100041, Jun. 2022, doi: 10.1016/j.dajour.2022.100041.
- [6] A. Soussi, E. Zero, R. Sacile, D. Trincherro, and M. Fossa, "Smart Sensors and Smart Data for Precision Agriculture: A Review," *Sensors*, vol. 24, no. 8, p. 2647, Apr. 2024, doi: 10.3390/s24082647.
- [7] Kudirat Bukola Adeusi, Ayodeji Enoch Adegbola, Prisca Amajuoyi, Mayokun Daniel Adegbola, and Lucky Bamidele Benjamin, "The potential of IoT to transform supply chain management through enhanced connectivity and real-time data," *World J. Adv. Eng. Technol. Sci.*, vol. 12, no. 1, pp. 145–151, May 2024, doi: 10.30574/wjaets.2024.12.1.0202.
- [8] T. Bosona and G. Gebresenbet, "The Role of Blockchain Technology in Promoting Traceability Systems in Agri-Food Production and Supply Chains," *Sensors*, vol. 23, no. 11, p. 5342, Jun. 2023, doi: 10.3390/s23115342.
- [9] M. K. Senapaty, A. Ray, and N. Padhy, "IoT-Enabled Soil Nutrient Analysis and Crop Recommendation Model for Precision Agriculture," *Computers*, vol. 12, no. 3, p. 61, Mar. 2023, doi: 10.3390/computers12030061.
- [10] M. Padhiary, A. K. Kyndiah, R. Kumar, and D. Saha, "Exploration of electrode materials for in-situ soil fertilizer concentration measurement by electrochemical method," *Int. J. Adv. Biochem. Res.*, vol. 8, no. 4, pp. 539–544, Jan. 2024, doi: 10.33545/26174693.2024.v8.i4g.1011.

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- [11] J. Del Cerro, C. Cruz Ulloa, A. Barrientos, and J. De León Rivas, "Unmanned Aerial Vehicles in Agriculture: A Survey," *Agronomy*, vol. 11, no. 2, p. 203, Jan. 2021, doi: 10.3390/agronomy11020203.
- [12] M. Padhiary, "The Convergence of Deep Learning, IoT, Sensors, and Farm Machinery in Agriculture," in *Designing Sustainable Internet of Things Solutions for Smart Industries*, IGI Global, 2025, pp. 109–142. doi: 10.4018/979-8-3693-5498-8.ch005.
- [13] M. F. Mail, J. M. Maja, M. Marshall, M. Cutulle, G. Miller, and E. Barnes, "Agricultural Harvesting Robot Concept Design and System Components: A Review," *AgriEngineering*, vol. 5, no. 2, pp. 777–800, Apr. 2023, doi: 10.3390/agriengineering5020048.
- [14] L. Blank, G. Rozenberg, and R. Gafni, "Spatial and temporal aspects of weeds distribution within agricultural fields – A review," *Crop Prot.*, vol. 172, p. 106300, Oct. 2023, doi: 10.1016/j.cropro.2023.106300.
- [15] M. Padhiary, D. Saha, R. Kumar, L. N. Sethi, and A. Kumar, "Enhancing Precision Agriculture: A Comprehensive Review of Machine Learning and AI Vision Applications in All-Terrain Vehicle for Farm Automation," *Smart Agric. Technol.*, vol. 8, p. 100483, Jun. 2024, doi: 10.1016/j.atech.2024.100483.
- [16] M. Sekhar, D. R. VijayKumar, and W. Khan, "Advances in Remote Sensing for Monitoring Crop Health and Yield Prediction," vol. 2, no. 12, 2024.
- [17] A. Kowalska and H. Ashraf, "Advances in Deep Learning Algorithms for Agricultural Monitoring and Management," 2023.
- [18] D. Saha, M. Padhiary, J. A. Barbhuiya, T. Chakrabarty, and L. N. Sethi, "Development of an IOT based Solenoid Controlled Pressure Regulation System for Precision Sprayer," *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 11, no. 7, pp. 2210–2216, 2023, doi: 10.22214/ijraset.2023.55103.
- [19] A. Upadhyay, S. G C, Y. Zhang, C. Koparan, and X. Sun, "Development and evaluation of a machine vision and deep learning-based smart sprayer system for site-specific weed management in row crops: An edge computing approach," *J. Agric. Food Res.*, vol. 18, p. 101331, Dec. 2024, doi: 10.1016/j.jafr.2024.101331.
- [20] M. Padhiary, N. Rani, D. Saha, J. A. Barbhuiya, and L. N. Sethi, "Efficient Precision Agriculture with Python-based Raspberry Pi Image Processing for Real-Time Plant Target Identification," *Int. J. Res. Anal. Rev.*, vol. 10, no. 3, pp. 539–545, 2023, doi: <http://doi.one/10.1729/Journal.35531>.
- [21] A. Jafar, N. Bibi, R. A. Naqvi, A. Sadeghi-Niaraki, and D. Jeong, "Revolutionizing agriculture with artificial intelligence: plant disease detection methods, applications, and their limitations," *Front. Plant Sci.*, vol. 15, Mar. 2024, doi: 10.3389/fpls.2024.1356260.
- [22] "Digital Twin-Based Crop Yield Prediction in Agriculture," in *Advances in Business Information Systems and Analytics*, IGI Global, 2024, pp. 99–110. doi: 10.4018/979-8-3693-3234-4.ch008.
- [23] F. Ali, A. Rehman, A. Hameed, S. Sarfraz, N. A. Rajput, and M. Atiq, "Climate Change Impact on Plant Pathogen Emergence: Artificial Intelligence (AI) Approach," in *Plant Quarantine Challenges under Climate Change Anxiety*, K. A. Abd-Elsalam and S. M. Abdel-

Momen, Eds., Cham: Springer Nature Switzerland, 2024, pp. 281–303. doi: 10.1007/978-3-031-56011-8_9.

[24] S. Adinarayana, M. G. Raju, D. P. Srirangam, D. S. Prasad, M. R. Kumar, and S. B. Veeram, "Enhancing Resource Management in Precision Farming through AI-Based Irrigation Optimization," in *How Machine Learning is Innovating Today's World*, 1st ed., A. Dey, S. Nayak, R. Kumar, and S. N. Mohanty, Eds., Wiley, 2024, pp. 221–251. doi: 10.1002/9781394214167.ch15.

[25] K. Pachiappan, K. Anitha, R. Pitchai, S. Sangeetha, T. V. V. Satyanarayana, and S. Boopathi, "Intelligent Machines, IoT, and AI in Revolutionizing Agriculture for Water Processing," in *Advances in Computational Intelligence and Robotics*, B. B. Gupta and F. Colace, Eds., IGI Global, 2023, pp. 374–399. doi: 10.4018/978-1-6684-9999-3.ch015.

[26] I. Raza *et al.*, "Precision Nutrient Application Techniques to Improve Soil Fertility and Crop Yield: A Review with Future Prospect," vol. 05, no. 08, 2023.

[27] M. Padhiary, "Bridging the gap: Sustainable automation and energy efficiency in food processing," *Agric. Eng. Today*, vol. 47, no. 3, pp. 47–50, 2023, doi: <https://doi.org/10.52151/aet2023473.1678>.

[28] L. Silva, L. A. Conceição, F. C. Lidon, M. Patanita, P. D'Antonio, and C. Fiorentino, "Digitization of Crop Nitrogen Modelling: A Review," *Agronomy*, vol. 13, no. 8, p. 1964, Jul. 2023, doi: 10.3390/agronomy13081964.

[29] E. Ramazanoglu, "Effects of vermicompost application on plant growth and soil enzyme activity in wheat (*Triticum aestivum* L.) monitored by thermal imaging," *Cogent Food Agric.*, vol. 10, no. 1, p. 2373872, Dec. 2024, doi: 10.1080/23311932.2024.2373872.

[30] Y. Edan, G. Adamides, and R. Oberti, "Agriculture Automation," in *Springer Handbook of Automation*, S. Y. Nof, Ed., in Springer Handbooks. , Cham: Springer International Publishing, 2023, pp. 1055–1078. doi: 10.1007/978-3-030-96729-1_49.

[31] M. Padhiary, S. V. Tikute, D. Saha, J. A. Barbhuiya, and L. N. Sethi, "Development of an IOT-Based Semi-Autonomous Vehicle Sprayer," *Agric. Res.*, vol. 13, no. 3, Jun. 2024, doi: 10.1007/s40003-024-00760-4.

[32] A. Srivastava and J. Prakash, "Techniques, Answers, and Real-World UAV Implementations for Precision Farming," *Wirel. Pers. Commun.*, vol. 131, no. 4, pp. 2715–2746, Aug. 2023, doi: 10.1007/s11277-023-10577-z.

[33] M. Mohan *et al.*, "UAV-Supported Forest Regeneration: Current Trends, Challenges and Implications," *Remote Sens.*, vol. 13, no. 13, p. 2596, Jul. 2021, doi: 10.3390/rs13132596.

[34] S. Mishra, "Emerging Technologies—Principles and Applications in Precision Agriculture," in *Data Science in Agriculture and Natural Resource Management*, vol. 96, G. P. O. Reddy, M. S. Raval, J. Adinarayana, and S. Chaudhary, Eds., in Studies in Big Data, vol. 96. , Singapore: Springer Singapore, 2022, pp. 31–53. doi: 10.1007/978-981-16-5847-1_2.

[35] M. Padhiary, "Status of Farm Automation, Advances, Trends, and Scope in India," *Int. J. Sci. Res. IJSR*, vol. 13, no. 7, pp. 737–745, Jul. 2024, doi: 10.21275/SR24713184513.

- [36] T. Ayoub Shaikh, T. Rasool, and F. Rasheed Lone, "Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming," *Comput. Electron. Agric.*, vol. 198, p. 107119, Jul. 2022, doi: 10.1016/j.compag.2022.107119.
- [37] K. Jha, A. Doshi, P. Patel, and M. Shah, "A comprehensive review on automation in agriculture using artificial intelligence," *Artif. Intell. Agric.*, vol. 2, pp. 1–12, Jun. 2019, doi: 10.1016/j.aiia.2019.05.004.
- [38] R. Chithra, Vasantheeswaran. R, T. A.P, and Thangavel. G, "Enhancing Agricultural Efficiency and Sustainability Through Advanced IoT and AI-Driven Precision Farming Technologies," in *2024 International Conference on Electronics, Computing, Communication and Control Technology (ICECCC)*, Bengaluru, India: IEEE, May 2024, pp. 1–5. doi: 10.1109/ICECCC61767.2024.10593925.
- [39] H. Mehmood, D. Liao, and K. Mahadeo, "A Review of Artificial Intelligence Applications to Achieve Water-related Sustainable Development Goals," in *2020 IEEE / ITU International Conference on Artificial Intelligence for Good (AI4G)*, Geneva, Switzerland: IEEE, Sep. 2020, pp. 135–141. doi: 10.1109/AI4G50087.2020.9311018.
- [40] "Crop Yield Prediction Using Artificial Intelligence and Remote Sensing Methods," in *Advances in Geographical and Environmental Sciences*, Singapore: Springer Nature Singapore, 2024, pp. 103–117. doi: 10.1007/978-981-97-0341-8_6.
- [41] "Enhancing Resource Management in Precision Farming through AI-Based Irrigation Optimization," in *How Machine Learning is Innovating Today's World*, 1st ed., Wiley, 2024, pp. 221–251. doi: 10.1002/9781394214167.ch15.
- [42] E. M. B. M. Karunathilake, A. T. Le, S. Heo, Y. S. Chung, and S. Mansoor, "The Path to Smart Farming: Innovations and Opportunities in Precision Agriculture," *Agriculture*, vol. 13, no. 8, p. 1593, Aug. 2023, doi: 10.3390/agriculture13081593.
- [43] E. E. K. Senoo *et al.*, "IoT Solutions with Artificial Intelligence Technologies for Precision Agriculture: Definitions, Applications, Challenges, and Opportunities," *Electronics*, vol. 13, no. 10, p. 1894, May 2024, doi: 10.3390/electronics13101894.
- [44] A. Soussi, E. Zero, R. Sacile, D. Trincherro, and M. Fossa, "Smart Sensors and Smart Data for Precision Agriculture: A Review," *Sensors*, vol. 24, no. 8, p. 2647, Apr. 2024, doi: 10.3390/s24082647.
- [45] H. A. D. Nguyen and Q. P. Ha, "Robotic autonomous systems for earthmoving equipment operating in volatile conditions and teaming capacity: a survey," *Robotica*, vol. 41, no. 2, pp. 486–510, Feb. 2023, doi: 10.1017/S0263574722000339.
- [46] S. Tiwari, B. Bhardwaj, D. Arora, and S. Khatri, "Challenges and Barriers to Smart Farming Adaptation: A Technical, Economic, and Social Perspective," in *Smart Agritech*, 1st ed., S. K. Srivastava, D. Srivastava, K. Cengiz, and P. Gaur, Eds., Wiley, 2024, pp. 75–111. doi: 10.1002/9781394302994.ch4.
- [47] S. Pearson, P. Chudleigh, S. Simpson, and N. Schofield, "Learning to invest better: Using ex post investment analysis on agri-environmental research and development," *Res. Eval.*, vol. 21, no. 2, pp. 136–151, Jun. 2012, doi: 10.1093/reseval/rvs008.

- [48] G. Ali, M. M. Mijwil, Bosco Apparatus Buruga, M. Abotaleb, and I. Adamopoulos, "A Survey on Artificial Intelligence in Cybersecurity for Smart Agriculture: State-of-the-Art, Cyber Threats, Artificial Intelligence Applications, and Ethical Concerns," *Mesopotamian J. Comput. Sci.*, vol. 2024, pp. 71–121, Jul. 2024, doi: 10.58496/mjcs/2024/007.
- [49] A. S. George, A. S. H. George, and T. Baskar, "Edge Computing and the Future of Cloud Computing: A Survey of Industry Perspectives and Predictions," vol. 02, no. 02, 2023.
- [50] A. Kristian, T. Sumarsan Goh, A. Ramadan, A. Erica, and S. Visiana Sihotang, "Application of AI in Optimizing Energy and Resource Management: Effectiveness of Deep Learning Models," *Int. Trans. Artif. Intell. Ital.*, vol. 2, no. 2, pp. 99–105, Jun. 2024, doi: 10.33050/italic.v2i2.530.
- [51] V. T. Shalini, R. Neware, T. Kumari, and M. Kumar, "Soil Health Management Using Artificial Intelligence for Smart Agriculture Systems," Sep. 09, 2024, *MDPI AG*. doi: 10.20944/preprints202409.0605.v1.
- [52] V. Balaska, Z. Adamidou, Z. Vryzas, and A. Gasteratos, "Sustainable Crop Protection via Robotics and Artificial Intelligence Solutions," *Machines*, vol. 11, no. 8, p. 774, Jul. 2023, doi: 10.3390/machines11080774.
- [53] S. Singh, R. Vaishnav, S. Gautam, and S. Banerjee, "Agricultural Robotics: A Comprehensive Review of Applications, Challenges and Future Prospects," in *2024 2nd International Conference on Artificial Intelligence and Machine Learning Applications Theme: Healthcare and Internet of Things (AIMLA)*, Namakkal, India: IEEE, Mar. 2024, pp. 1–8. doi: 10.1109/AIMLA59606.2024.10531517.
- [54] M. Padhiary, R. Kumar, and L. N. Sethi, "Navigating the Future of Agriculture: A Comprehensive Review of Automatic All-Terrain Vehicles in Precision Farming," *J. Inst. Eng. India Ser. A*, Jun. 2024, doi: 10.1007/s40030-024-00816-2.
- [55] U. Avalekar, Dr. J. Patil, Dr. S. Patil, Prof. (Dr.) J. Khot, and Prof. (Dr.) K. Prathapan, "Optimizing Agricultural Efficiency: A Fusion of IoT, AI, Cloud Computing, and Wireless Sensor Network," 2024, *Elsevier BV*. doi: 10.2139/ssrn.4789232.
- [56] Dr. A. Shaji George, "5G-Enabled Digital Transformation: Mapping the Landscape of Possibilities and Problems," Jun. 2024, doi: 10.5281/ZENODO.11583365.
- [57] Dr. M. M. Dr. Pankaj Mudholkar, "Empowering Agricultural Ecosystems: Leveraging 5G IoT for Enhanced Product Integrity and Sustainable Ecological Environments," *J. Inform. Educ. Res.*, vol. 4, no. 1, Feb. 2024, doi: 10.52783/jier.v4i1.605.
- [58] M. Padhiary, J. A. Barbhuiya, D. Roy, and P. Roy, "3D Printing Applications in Smart Farming and Food Processing," *Smart Agric. Technol.*, vol. 9, p. 100553, Aug. 2024, doi: 10.1016/j.atech.2024.100553.
- [59] M. Padhiary and P. Roy, "Advancements in Precision Agriculture: Exploring the Role of 3D Printing in Designing All-Terrain Vehicles for Farming Applications," *Int. J. Sci. Res.*, vol. 13, no. 5, pp. 861–868, 2024.
- [60] G. S. Mmbando, "Omics: A new, promising technologies for boosting crop yield and stress resilience in African agriculture," *Plant Stress*, vol. 11, p. 100366, Mar. 2024, doi: 10.1016/j.stress.2024.100366.

- [61] A. Chaudhry *et al.*, "The changing landscape of agriculture: role of precision breeding in developing smart crops," *Funct. Integr. Genomics*, vol. 23, no. 2, Jun. 2023, doi: 10.1007/s10142-023-01093-1.
- [62] "Harnessing AI and GIS Technologies for Climate-Resilient Agriculture and Environmental Sustainability," in *Practice, Progress, and Proficiency in Sustainability*, IGI Global, 2024, pp. 333–364. doi: 10.4018/979-8-3693-6336-2.ch013.
- [63] N. Raina, M. Zavalloni, and D. Viaggi, "Incentive mechanisms of carbon farming contracts: A systematic mapping study," *J. Environ. Manage.*, vol. 352, p. 120126, Feb. 2024, doi: 10.1016/j.jenvman.2024.120126.
- [64] M. Padhiary, "Harmony under the Sun: Integrating Aquaponics with Solar-Powered Fish Farming," in *Introduction to Renewable Energy Storage and Conversion for Sustainable Development*, vol. 1, AkiNik Publications, 2024, pp. 31–58. [Online]. Available: <https://doi.org/10.22271/ed.book.2882>
- [65] M. Padhiary, "Membrane Technologies for Treating Wastewater in the Food Processing Industry: Practices and Challenges," in *Research Trends in Food Technology and Nutrition*, vol. 27, AkiNik Publications, 2024, pp. 37–62. doi: 10.22271/ed.book.2817.
- [66] T. Bosona and G. Gebresenbet, "The Role of Blockchain Technology in Promoting Traceability Systems in Agri-Food Production and Supply Chains," *Sensors*, vol. 23, no. 11, p. 5342, Jun. 2023, doi: 10.3390/s23115342.
- [67] P. R. Kothamali, N. Mandaloju, N. Srinivas, and S. S. M. Dandyala, "Ensuring Supply Chain Security and Transparency with Blockchain and AI," vol. 14, no. 01, 2023.