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INNOVATION IN AGRICUTURAL PRACTICES USING AI AND MACHINE LEARNING

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Abstract
This study examines how artificial intelligence (AI) can revolutionize agriculture by tackling pressing issues including food security, climate variability, and resource inefficiency. It emphasizes how artificial intelligence (AI) facilitates data-driven decision-making for effective and sustainable farming methods. The review explores at AI developments and uses, with particular attention to blockchain, IoT, and machine learning (ML). Precision farming, crop management, and post-harvest logistics are examined in relation to these technologies, with a focus on improving sustainability and resource efficiency. Artificial intelligence (AI) has shown great promise in transforming agricultural methods and providing answers to increase sustainability and output. Obstacles including high prices, a lack of technical know-how, and infrastructure deficiencies, especially for smallholder farmers, prevent its widespread implementation. The study highlights the need for AI solutions that are affordable, inclusive, and flexible in order to help smallholder farmers close the gap. It emphasizes how crucial ethical and regulatory frameworks are to guaranteeing fair access and scalability of AI technology in agriculture. This study suggests future directions for innovation while highlighting the innovative role of AI in handling global agriculture challenges. The report adds to the conversation on using AI to create a resilient and just agriculture sector by highlighting inclusion and sustainable growth.

Keywords: *AI in Agriculture; Machine Learning; Precision Farming; Agricultural Innovation; Sustainable Farming.*

1.Introduction

The global population is predicted to approach 10 billion people by 2050, and in order to feed them, agriculture must be increased by 50%. Currently, farming occupies around 38% of the land area (1). Since agriculture contributes a major part in the economic prosperity of most countries, it is crucial for rural development and job creation. In nations like India, where the agricultural sector accounts for a large portion of gross domestic product [GDP] (about 18%), agricultural advancements has significantly increased per capita rural earning and employed over half of the workforce (2). Automation of agriculture is essential since it is a delicate economic sector that depends on other industries. This will encourage rural development, which will then result in structural and rural transformation (3).

John McCarthy, initially used the term "artificial intelligence" in 1956. Computer science research is heavily focused on artificial intelligence (AI) because of its rapid technological development and practicality (4). In the fields of medicine, agriculture, education, business, industry, and security, artificial intelligence has made inroads. To achieve automation in agriculture, artificial intelligence is crucial. Farmers must put in a great deal of work and be persistent and persistent. One of the main causes of farmer depression and suicides is the significant financial losses that farmers suffer due to low revenue, erratic weather patterns, or resource scarcity (5). Due to traditional agriculture's time-consuming and energy-draining nature, the primary cause of farmer suicides is the absence of a supplementary employment. By lowering duration commitment, labor costs, and improving yield and productivity, AI can address these issues, improving farmers' quality of life and, ideally, lowering the number of farmer suicides (6).

Technological developments in deep learning (DL), machine learning (ML), internet of things (IoT), machine vision, and neural networks (NN), improve the use of artificial intelligence (AI) (7). Because of technological advancements like robotics, humidity and thermal sensors, drones, machinery, GPS innovation, and information improvement, agriculture and technology have become complementary in today's globe. Agriculture is now consistently profitable, safe, and environmentally beneficial as a result (8). Unmanned aerial vehicles (UAVs), satellites, and remote sensing can gather data throughout the day across a whole field to monitor temperature, plant health, soil condition, and other factors. AI simplifies problem-solving through a variety of recently developed logics and techniques, such as Expert Systems (ES), Fuzzy Logic (FL), Neuro-Fuzzy Logic, and Artificial Neural Networks (ANN), which are the most popular for research. An artificial neural network (ANN) is a mathematical and computing processing technique which mimics neurons in the human brain to learn, reason, make decisions, and solve issues. An artificial neural network (ANN) is a task-based operating system which relies on built-in tasks rather than typical computationally coded tasks. It can use ANN to find the best-fit solution for a problem and capture fine details (9).

Various algorithms, such as the dynamic adaption, Silva and Almeida's algorithm, Rprop, Quickprop, Delta-bar-delta algorithm, as well others, are employed for training depending on their intended usage. The process uses nine neurons.

With hardware-built memory-chip systems that have software installed to apply algorithms and logic-based concepts, embedded systems serve as a hardware-software interface. Three layers together create the ANN architecture: the input layer, the hidden layer, and the output layer **(Figure 1).**

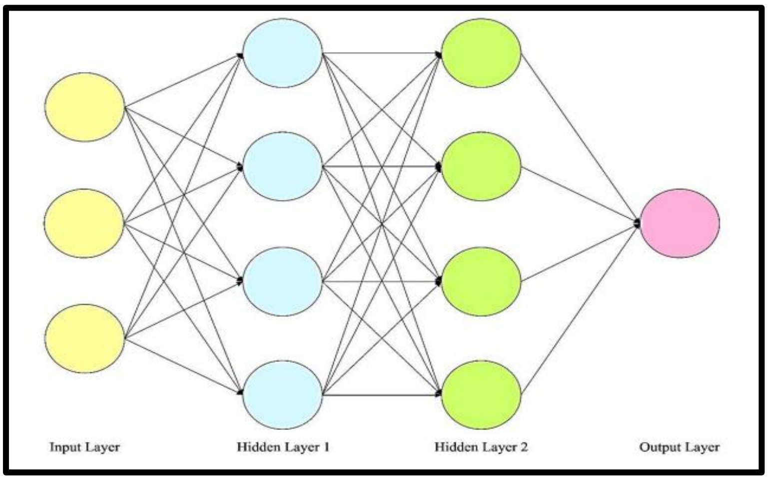

Figure 1: Artificial Neural Network Diagrammatic Representation (10)

1.1. Applications of Artificial intelligence [AI] and [ML] Machine Learning in Agricultural Practices

1.1.1. Precision farming and data-driven decisions

Precision agriculture enhances crop quality, production, food protection, and the agricultural- based economy while minimizing environmental damage. The technologies used in PA nowadays include Global Navigation Satellite Systems (GNSS), RS, GIS along with sensors that work together to help with water conservation, harvesting, planting, spraying, laser field leveling, and different fertilizer application rates **(Figure 2)** (11)**.** Since seeding has a direct impact on crop development, yield, and germination, it is crucial to agricultural production. The foundation of PA progress is precision planting, which is also essential for promoting other precision applications including as irrigation, harvesting, and fertilizer application. Land quality affects seeding. It is capable of improving production rate, seed protection, enhance population density, boost crop productive yields, and lower labor costs, all of which improve farm earnings. Precision planting and exact leveling are made possible by laser land-leveling machines, which also effectively improve agriculture conditions. It can boost crop yields, enhance the effectiveness of fertilizer and irrigation, and so boost economic gains (12). This Precision Agriculture (PA) system uses a three-layer architecture, which is represented from bottom to top in **Figure 3** and consists of a layer to sense data, cloud service layer, along with user interface layer. Temperature, moisture, light intensity, and the gas concentrations of carbon dioxide, oxygen, ozone, and nitrogen dioxide are all compiled by the data sensing layer. Data sensing devices use the TCP Socket protocol to upload real-time data to the cloud **(Figure 4).** Additionally, there are features for real-time viewing and video data storage. The Cloud Service Layer offers user-oriented application services, data preservation and maintenance, and analysis services. MySQL is used to store the data, which is then archived for Hadloop HDFS analysis. The User Interface Layer handles the Android and web user interfaces (13).

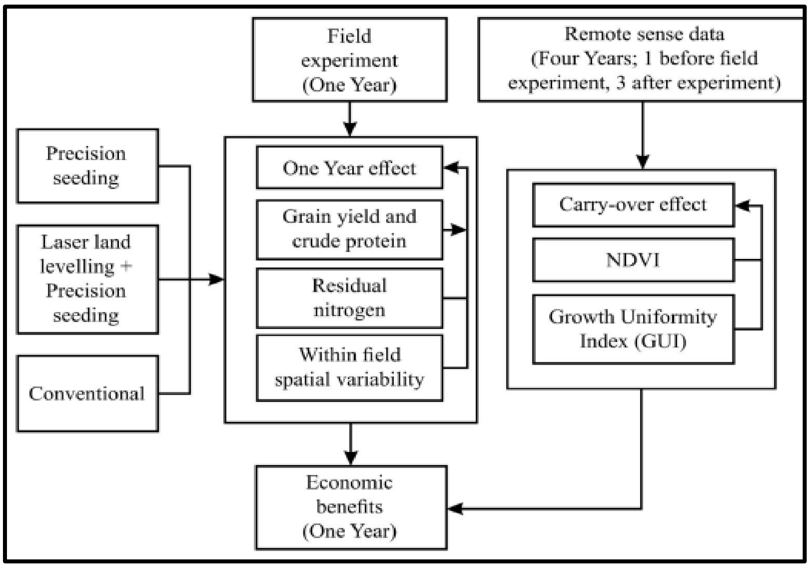

Figure 2. Precision Study Flow Diagram.

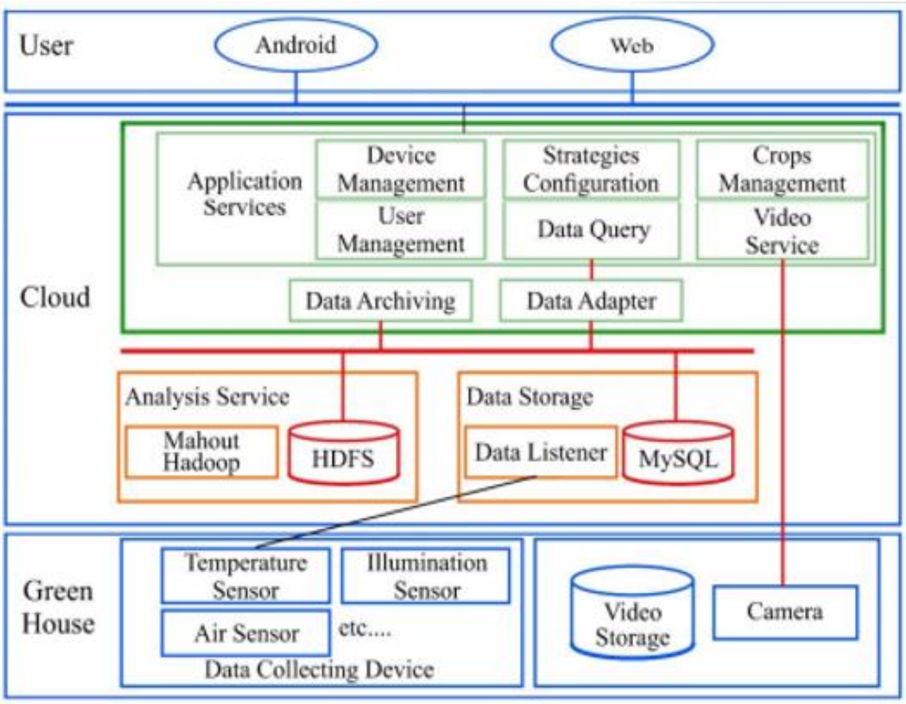

Figure 3. Precision Agriculture System Architecture (14)

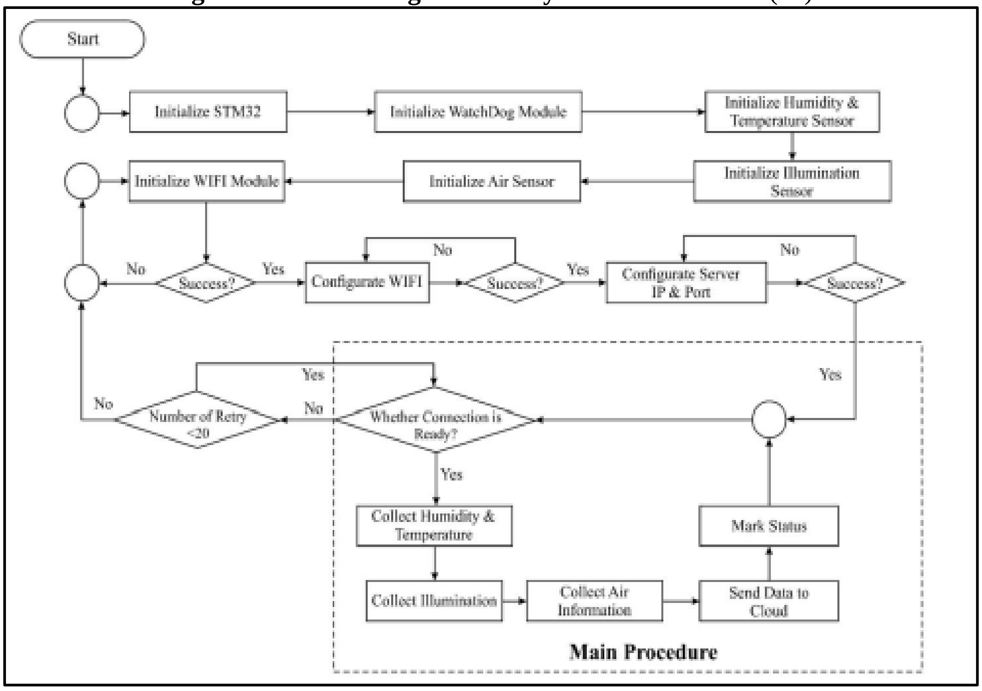

Figure 4. Workflow diagram for data collection equipment (15)

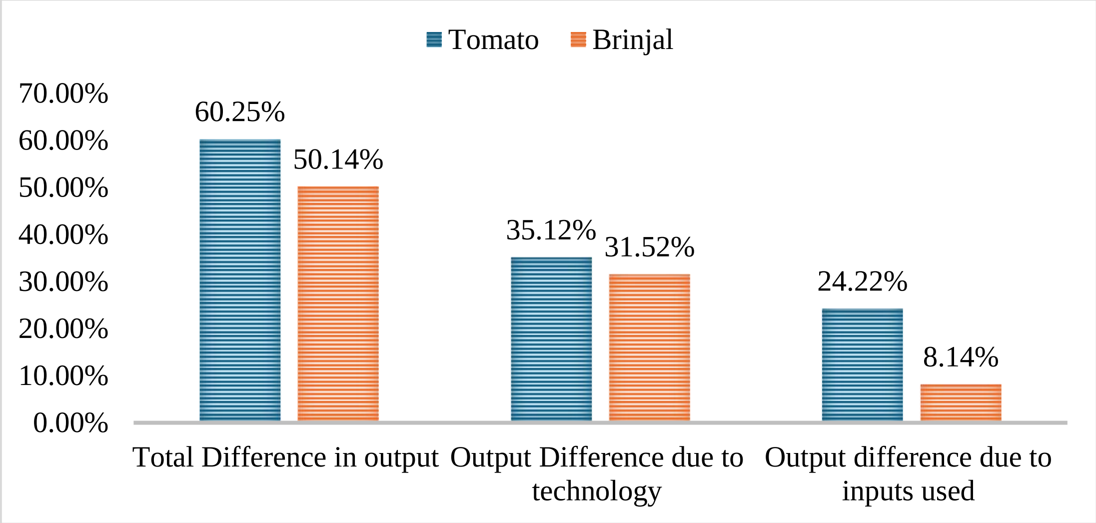

Figure 6: Comparing the production of tomatoes and brinjal through precision and imprecision farming (5)

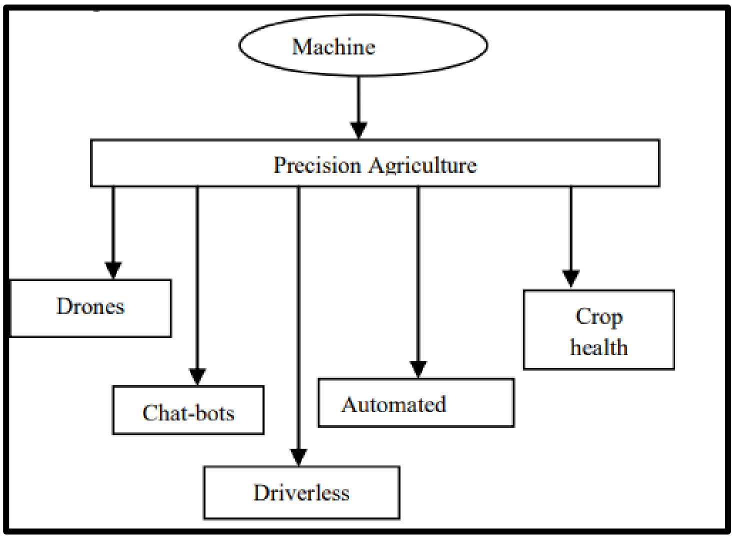

Figure 7: Solutions to Precision agriculture

1.1.2. Crop Growth Environment Monitoring

The design of crop growth environment monitoring involves the use of IoT, which is only used in agriculture, to sense, transmit, and compute different environmental data. Real-time data on temperature, atmospheric CO2, and humidity—all of which have a direct impact on agriculture—must be gathered by sensors (16). In order for microcontrollers that belong to data aggregation points and wireless sensors to gather all the details in real time, combine it, and assist in the aggregation of environmental data, a radio frequency of 433 MHz was employed to communicate the data. MSP430F149 and LPC2478 was employed individually. Originally operating at 780 MHz, a WSN was developed that was compatible with IEEE 802.15.4c environmental monitoring, which was systemized for millet cultivation. Real-time temperature and soil moisture monitoring, which have an impact on crop development, was done using RFID technology (17). A system for analyzing soil was created that might offer a trustworthy source of information for learning more about the growth and development of plants. Gathering data on wheat cultivation and other ecological factors aided for the creation of an Internet of Things operation that can primarily be used to diagnose wheat sowing conditions. Understanding the environment of agricultural monitoring dynamics from point to surface required the use of a geographic information system, or GIS. ZigBee was able to compile data on the sensor network's sensing nodes, which helped with the real-time collection of temperature, humidity, and CO2 concentration data (18).

1.1.3. Soil health analysis and management

By facilitating accurate, data-centric approaches, AI and ML are transforming soil health management (19). Artificial intelligence (AI) systems are able to analyze soil factors like pH levels, nutrient content, moisture levels, and organic matter by utilizing sophisticated sensors, remote sensing, and satellite photography (20). By identifying inadequacies and imbalances in soil composition, farmers can implement targeted interventions with the use of these findings. In order to ensure long-term sustainability, machine learning algorithms can also forecast how various agricultural methods would affect soil health (21). Additionally, AI-powered solutions reduce waste and environmental effect by providing advice for crop rotation and fertilizer application strategies based on particular soil conditions (22). By improving soil fertility while preserving ecological balance, these advances assist farmers in increasing output and guaranteeing resource-efficient agriculture (23).

1.1.4. Irrigation management through AI

Water is a crucial component of agricultural production since it is necessary for the growth and development of crops, despite its scarcity in today's world (24). Artificial intelligence (AI) has made it possible to replace labor-intensive and water-wasting traditional irrigation systems with automated ones that don't require human interaction (25). It also helps crops become more resistant to lodging, which results in a good yield. The intelligent water-saving irrigation system that uses ANN enhanced drainage and irrigation efficiency. In order to effectively manage irrigation scheduling, a sensor system that can determine the water content of various soil layers and transmit pre-programmed user commands to actuators to turn sprinklers on and off is necessary (26).

1.1.5. Pest and weed control management

Weed Management

Weeds are an unwanted, invasive, and harmful plant that hinders the growth of other crop plants and continuously impacts farmers' agricultural productivity, earnings, and the nation's economy (27). Due to their competition for light, nourishment and moisture, interference alongside crop harvesting machinery, negative effects on water resources and the natural ecology, and health problems for both humans and animals, weeds hinder the correct development of crops (Ministry of Agriculture, Land and Fisheries, 2020)(28). When compared to computerized weed identification and categorization, traditional weed management techniques are far too ineffective (29). The use of weedicides can pollute the environment and have a harmful effect on public health. By accurately spraying the target area, AI-based weed detection systems can save expenses and crop damage (30).

Disease and Pest Management

Diseases are caused by a variety of factors, including genetics, the type of soil, climate conditions, temperature, etc., because they are unpredictable, large-scale commercial farming is difficult (31). To efficiently manage diseases and limit deficits in more efficient manner and for economically affordability, farmers must use AI to build an integrated disease management model that incorporates all three chemical, physical, and biological factors (32). Field-based agricultural disease identification using farmers' smartphones is becoming more feasible thanks to AI-based image recognition technologies that can precisely identify some plant diseases (33).

The disease detection process involves a number of steps, such as plant imaging, which makes sure that images of leaves are separated from the backdrop and show both infected and uninfected portions of the leaf segment; enhanced processing, that removes the infected portion; shift to a lab; identification of diseases or pests; and deficient nutrient monitoring, among others (34). Pests are annoying annoyances for farmers that negatively impact agricultural productivity and the world economy (35). In order to detect illnesses, pests, abnormal crop degradation, or dead soil, pest control firms employ drones to virtually visit farms and provide round-the-clock monitoring. A farmer can collect data from any crop area and take appropriate action. In contrast to the long-term abuse of pesticides, integrated pest management, or IPM, is a sustainable approach for pest management (36).

1.1.6. Yield prediction and optimization

Yield prediction and enhancement are being revolutionized by AI and ML through precise forecasting and resource management (37). With the use of historical and current understanding on weather, soil condition, crop development phases, along with insect invasions, ML methodologies predict yields with high precision (38). Farmers are able to increase yields, minimize losses, and improve planning thanks to these forecasts. Additionally, by using predictive analytics to make suggestions for seed choices, planting dates, and irrigation schedules, AI systems improve farming methods (39). AI-powered drones and Internet of Things devices allow farmers to keep a close eye on crop health, spot stress areas, and take swift corrective action (40) Profitability is increased and sustainable agriculture is supported by this data-driven strategy, which guarantees larger yields with less resource input (41).

1. Methodology

The research approach focuses on the new technologies that can be used to offer a good substitute for the agricultural practices of today. There are three sections to the study. Machine learning and precision agriculture are covered in Section 1, findings and conclusion are covered in Section 2, and conclusion and future scope are covered in Section 3 (42).

2.1. Machine learning cognitive technology

The area of computing science and artificial intelligence that emphasizes on developing processes with self-learning capabilities is called machine learning. To solve the daily activities, machine learning is employed to create accurate and efficient systems that can assess a far larger array of tasks (43). With a view to assess how a particular variety could fare in various subclimates, soil types, weather patterns, and other conditions, scientists can run early crop experiments using computer models. Physical field trials are not replaced by this computerized testing, but it does help plant breeders forecast crop performance more precisely (44).

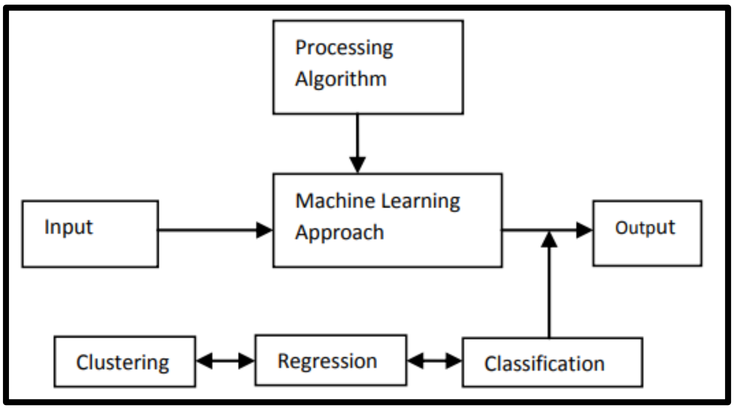

Figure 5: Diagram of data processing for machine learning (45)

A supervised or unsupervised machine learning technique, like a SVM operator, Bayesian network, convolution neural model (CNN), or another type, uses information on the crop variety to be evaluated as input (46). The method examines the input to extract pertinent information and features pertaining to the issue at hand. The processing algorithm analyzes the data based on the variables and functions set, and it produces a workable result that is regressed or categorized (47).

2.2. Impact of Precision Agriculture

Using cognitive technology in agriculture could make it easier to choose the optimum crop for various climates and better meet the needs of farmers (48). To do this, data on seed types, weather, soil types, infestations in a particular location, disease probability, and information about what worked best, annually results, current market dynamics, prices, and consumer needs can be analyzed and compared. Then, farmers can decide how to optimize crop returns (49). It would seem that the farming sector is poised for a technical revolution, with AI serving as its leading force, given the rapid advancement of machine learning technologies (50).

2.3. Precision farming using machine learning technology

a. Chat bots for farmers

Conversational virtual assistants, or chatbots, automate user interactions. Chatbots are used in agriculture to facilitate communication between farmers, manufacturers, markets, and government players (52). In their early stages, chatbots were mostly utilized by media outlets, insurance companies, retail stores, and travel agencies. By helping farmers with their inquiries and offering suggestions and guidance on particular agricultural issues, agriculture might also benefit from this new technology. The cutting-edge mode will enable prompt and interactive remote crop monitoring (53).

b. Drones and unmanned aerial vehicles

Unpiloted aerial vehicles UAVs take pictures and gather information about a certain area. Widespread environmental monitoring and cheap operating costs are the results of UAV utilization (54). Productivity will be raised by offering innovative methods of raising crop yields through thorough analysis, long-distance crop spraying, and high efficiency. Drone technologies are rapidly winning farmers' trust. Since drone technology's useful applications are always developing, it's probable that drone-powered results will be increasingly widely accepted in the near years.

c. Driverless Tractors

It is a predicted future, robotic agriculture will not be fully deployed for some ten to fifteen years. All agricultural responsibilities are concluded autonomously by no-driver tractors. Sensors which hold out the important methods, observe on impediments, and determine where to apply farm inputs are fixed in them. Technology for autonomous vehicles has been adopted by numerous IT companies (55). These days, commercially techniques like GPS systems, radars and sensors are being combined with agriculture. Technological advancements in technology and software are opening up new opportunities for innovative farming, which will ease the load on an already overworked labor and enable farmers to work more acreage for longer periods of time (56).

d. Automated irrigation systems

Farmers are aware of how difficult it is to manage irrigation in the traditional manner. The use of automated irrigation systems and a strong emphasis on past weather patterns will help forecast the resources needed. Fortunately, real-time machine learning is incorporated into automated irrigation systems to regularly manage the optimal soil conditions and raise mean yields. This has the ability to lower production costs in addition to drastically reducing labor. Since 70% of the freshwater on Earth is used for agriculture, being able to manage it mindfully would have a significant impact on conserving water towers and reservoirs (57).

e. Crop health monitoring

The majority of traditional crop health monitoring methods are categorical and take a lot of time. The amount of data being collected is causing companies in the battle for 3D laser scanning and hyperspectral imaging to primarily boost their accuracy and precision (58). By using the deep learning method of machine learning, an alert-based system can enhance crop protection.

i. Indian Agriculture and scope for Artificial intelligence

Artificial Intelligence (AI) and its cognitive ramifications throughout sectors have been driven and promoted not just to drastically eliminate manual tasks but also to gradually and accurately forecast future occurrences (59). Agriculture has been constrained in the past ten years by the rise of technology-driven industries; yet, the introduction of artificial intelligence has made a chance to deal with challenges such as global warming and climate crises. This milestone has aided in adjusting to the growing complexity of contemporary farming. One of the most efficient and research-driven applications nowadays is farm analytics, which is powered by neural networks' cognitive capacity to process massive datasets (60).

The introduction of big data and sector-specific machine learning technologies can boost agricultural production, even if developing AI algorithms in an agricultural setting can be difficult. For a nation like India, where over 64% of the population still relies on direct agriculture and over 75% still depends on their livelihood, the future of AI in farming is very vital. In contrast to the west of India, agricultural issues cannot be resolved solely by sophisticated agritech solutions like yield multiplication and plant breeding because farming is still primarily dispersed and unorganized (61).

2.4. Challenges of in AI-Driven Agriculture Sector in India

The fact that AI has great potential for farming, creating AI algorithms in this environment can be difficult. Large and clean data chunks are necessary for the first and essential block to view an effective trained algorithms using a substantial total of agricultural spatial data. There are fewer study cycles because more adequate data is typically accessible during the growth season. Since most of our farmlands are still fragmented, it may be ambitious to collect data holistically or in a mass way. This is especially true in India, where data from remote areas and farmlands that do not fulfill minimum hectare criteria during surveys are frequently excluded (62). There are erratic weather patterns in the soil texture due to the constantly shifting climate. Despite all precautions, the massive influx of diseases and pests is yet unknown (63). Even when farmers and producers are ready for a large crop and feel safe from all harvests, nature's uncertainties are always present. In India, the same seed and fertilizer may have different results as in the United States (64). A few variables that could influence the variance are usually the amount of rain per unit of the planted crop, soil types, oil degradation patterns, daylight hours, temperature, and so on. No two surroundings will be precisely the same, which makes it far more difficult to test, validate, and successfully implement such technologies than in most other businesses. This is the issue with addressing growers' concerns (65).

2. Findings And Discussion

The study mentioned above was carried out, and positive outcomes were attained (66). The statistics report was taken from the Ministry of Agriculture in the state of Rajasthan. It has been noted that over half of the entire terrain remains unorganized (66). A lot of people employ mechanical instruments and human labor to help with agriculture (67). The following edges were formed in the growth rate comparison of brinjals and tomatoes, which are both extensively grown in this area (68).

Thus, the aforementioned findings demonstrate the wide range of applications for precision agriculture in other crops and vegetables.

Table1: Table of comparisons for AI-driven agriculture (69)

AI Driven agriculture	Difference in output	Difference in output due to technology	Difference in output due to inputs
With P.A	60.25%	35.61%	31.20%
Without P.A	30.20%	21.50%	8.00%
Margin Difference	40.80%	15.20%	20.15%

Table 2: Crop: yield forecasting table.

Article	Crop	Observed Features	Functionality	Models/ Algorithms	Results
(70)	Coffee	42 color characteristics in digital pictures of coffee fruits	Coffee fruit count on a coffee branch that is automated	SVM	Harvestable: (1) Ripe/overripe: visibility percentage of 82.54–87.83% (2) Semi-ripe: 68.25–85.36 percent visibility (1) Unripe: visibility percentage 76.91–81.39%; not harvestable
(71)	Cherry	Digital pictures with colors that show the background, leaves, trees, and cherry fruits	Finding cherry branches that have full foliage	BM/GNB	89.6% accuracy
(72)	Green citrus	Features of the image (from 20 × 20 pixel digital photos of unripe green citrus fruits) include brightness, smoothness, fineness, granularity, irregularity, line-likeness, regularity, coarseness, contrast, and directionality.	Determining the quantity of green, immature citrus fruit in an outdoor setting	SVM	80.4% accuracy

(73)	Grass	Red and NIR spectral bands, vegetation indices	Calculation of grassland biomass (kg dry matter/ha/day) for Moorepark and Grange, two managed grasslands in Ireland	ANN/ANFIS	Moorepark: R 2 = 0.85 RMSE = 11.07 Grange: R 2 = 0.76 RMSE = 15.35
(69)	Wheat	Normalized values of the satellite NDVI and online projected soil characteristics	Predicting wheat yield within field variation		81.65% accuracy
(74)	Tomato	RGB photos with high spatial resolution	Tomato detection using RGB photos taken by a UAV		Recall: 0.6066 Precision: 0.9191 F-Measure: 0.7308

3. Future Research Directions

3.1 Advanced Ai Models for Agriculture

Future studies must concentrate on creating complex AI models specifically suited for the agricultural industry, fusing automation, predictive analytics, and real-time data integration (75). These models ought to make use of sophisticated neural networks, such as convolutional and frequent neural models, which work on enormous datasets from satellite photography, drones, and Internet of Things devices (76). Current agricultural research will advance with the combination of adversarial training for disease resistance prediction and generative AI for crop development scenario simulation (77).

3.2 Sustainable and Resource-Efficient Technologies

Developing sustainable AI-driven solutions to problems like soil erosion, water scarcity, and climate change is a vital area for recent years research. Precision fertilization can reduce environmental effects, and AI-enabled systems can forecast evapotranspiration rates to optimize water consumption. Resource-efficient farming methods that support global sustainability goals will be ensured by research into AI and IoT devices powered by renewable energy (78).

3.3 Integration of Blockchain and AI

AI and blockchain technologies can be combined to guarantee agricultural supply chains' transparency and traceability (79). Future research can examine how blockchain technology can be used to securely share data among stakeholders while AI analyzes that data to enhance market connections, minimize waste, and optimize logistics. Global agricultural trade will be revolutionized by research into AI-powered smart contracts for real-time pricing and quality assurance (80).

3.4 AI-Driven Climate Resilience

Global agriculture is under serious risk from climate change, hence AI-powered adaptive systems are required (81). The development of AI models that mimic climatic situations and offer farmers practical insights, including crop diversification plans and real-time weather-based interventions, must be the main goal of research. It will be crucial to develop AI tools for reducing the effects of extreme weather occurrences, such as crop varieties resistant to drought and predictions of pest outbreaks (82).

3.5 Enhancing Smallholder Farmer Accessibility

Technology has advanced, small scale farmers frequently do not have reach to these developments. Future studies should focus on affordable, approachable AI systems that address the particular requirements of small-scale farmers (83). This includes creating offline-operating localized AI models and multilingual chatbots that may offer regionally specific agriculture advise. Low-cost sensor devices and AI-driven applications can democratize access and close the gap in technology (84).

3.6 Multi-Disciplinary Research Collaborations

Multidisciplinary research integrating agronomists, data scientists, and environmentalists is necessary for agricultural innovation utilizing AI and ML (85). Future research should examine how these fields might work together, for example, by merging AI and ecological studies to preserve biodiversity or genetic engineering and AI to create crops resistant to disease. Holistic solutions addressing the economic, social, and environmental aspects of agriculture will be made possible by collaborative research models (86).

3.7 Ethical and Policy Frameworks

Data privacy, ownership, and labor displacement are ethical issues that need to be addressed as AI uses in agriculture expand (87). In order to ensure equitable practices for all parties involved, research should concentrate on creating frameworks that strike a balance between ethical issues and technological innovation (88). By developing policies that support fair technology distribution, AI adoption subsidies, and investments in rural digital infrastructure, policy-driven research can assist governments in implementing AI in agriculture.

3.8 AI-Driven Post-Harvest Management

In agriculture, post-harvest losses continue to be a major problem. Post-harvest procedures could be completely transformed by research into AI-driven systems for logistics optimization, quality evaluation, and storage management. Food security and waste reduction are ensured by AI-powered inventory management and cold chain logistics systems that can forecast spoiling rates. Farmers can increase their market pricing by creating AI systems that evaluate crop quality using sensor and imaging data.

3.9 Human-AI Collaboration Models

A crucial topic for future study will be examining methods to improve human-AI cooperation in agriculture. In order to preserve traditional agricultural expertise and provide farmers with useful insights, AI systems should serve as facilitators rather than substitutes. Research on participatory design methodologies, in which farmers actively participate in the creation of AI systems, can guarantee contextual and cultural relevance (89).

3.10 Scaling AI for Global Food Security

Scaling AI technologies to meet global food security concerns should be the main emphasis of future research (90). The implementation of AI-powered monitoring systems for international agricultural policies, the development of scalable AI solutions for various agro-climatic zones, and the development of international collaborations will all contribute to the sustainable meeting of the world's expanding food demand. For researchers to have the greatest worldwide influence, cost and scalability must come first (91).

1. Conclusion

AI's use in agriculture is a paradigm shift that gives previously unheard-of chances to address persistent issues and improve the production and sustainability of the industry (92). AI technologies have revolutionized post-harvest management, precision farming, and climate resilience, all of which have improved agricultural practices and lessened the impacts of environmental change (93). However, there are certain difficulties in integrating these technologies, especially when it comes to assuring smallholder farmers' accessibility and resolving moral dilemmas including data privacy and labor displacement (94).

Inclusion, affordability, and scalability should be given highest priority in future developments of AI for agriculture to guarantee that technical breakthroughs are available to a wide range of stakeholders (95). Agriculture could undergo yet another transformation with the help of interdisciplinary partnerships, the creation of climate-resilient models, and the inclusion of blockchain technique with artificial intelligence. To further encourage responsible AI deployment and close the technological gap, strong ethical and policy guidelines will be necessary (96).

Artificial intelligence (AI) has a wider impact on world-wide food security and ecological sustainability in agriculture than just technological innovation (97). Through the resolution of existing constraints and the pursuit of the indicated future research avenues, the agricultural industry may fully utilize AI to set up a resilient and sustainable food system in the future (98).

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