**An Overview on Emerging Agri-tech Solutions for Sustainable Agricultural Development**

**Abstract**

One of the most crucial sectors for a nation's economic development is agriculture. More over 70% of Indians are employed in agriculture, which also accounts for around one-third of the nation's GDP. Issues pertaining to agriculture have consistently impeded the country's advancement towards realizing its full potential. Sustainable agriculture, which entails modernizing conventional farming methods, is the only workable answer to this problem. Therefore, in order to make farming smarter, the program plans to use automation and Internet of Things technology. The emergence of the fourth agricultural revolution, which is defined by data-driven and automated smart farming, presents chances to improve climate resilience and sustainability. Artificial intelligence (AI), robotics, remote sensing, and information and communication technologies (ICT), especially the Next Generation Internet of Things (NG-IoT), enable data-driven decision-making and agricultural activity optimization. This study examines new ICT developments in agriculture to give readers a thorough grasp of the opportunities and problems associated with using these technologies to achieve sustainable agriculture. Additionally, we stress the need of explainable AI and human-centered systems in attaining sustainability in agriculture, emphasizing the critical role that transparent decision-making and user-centric design will play in determining the direction of smart farming in the future. We conclude by presenting actual Greek projects that make use of several of the aforementioned technologies, demonstrating their exceptional performance in the field of smart agriculture and offering guidance for the future in terms of integrating human engagement, improving explainability, and reliability.

**Keywords**

Agriculture, Emerging technologies, Biofuels, Bioenergy, Artificial Intelligence

**Introduction**

As the world's main source of food production, agriculture has a crucial role in both economic growth and rural development, as well as public health and human well-being across society. As the world's need for food and water is predicted to rise, it is imperative to ensure a safe and resilient food supply in order to combat hunger and malnutrition worldwide.

 Land usage, the use of energy and water resources, greenhouse gas emissions that contribute to climate change, and biodiversity have all been significantly impacted by agriculture. 70% of the water used worldwide is used for agriculture, and agricultural practices contribute to soil health issues and water ecosystem pollution through chemicals like pesticides and fertilizers, as well as pharmaceuticals and pollutants of increasing concern (CEC). The world's population is expected to reach 9.5 billion people by 2050, and in order to meet the need for food, feed, and fiber, it is anticipated that current agricultural production would rise by up to 70% [1]. The prevalence of chronic hunger and malnutrition is currently over 35% of the world's population. Reduced annual yields are the result of both the climate's continuous change and the stress conditions that crop plants are mostly experiencing [2]. Global crop production is being negatively impacted by ongoing climate change, mostly due to increased greenhouse gas emissions, the discharge of pollutants into soil and water, and overuse of natural resources. Due to urbanization and the expansion of industry, the land and water resources used for agriculture are continuously degrading. The extraordinary rise in global temperatures is mostly to blame for the current drought, erratic rainfall patterns, and intense heat waves. For every unit increase in the global average temperature, there has been a recorded 7% decrease in cereal and pulse yields worldwide [3]. Global food security appears to be in danger due to the comprehensive consequences of climate change, which are disrupting agricultural output [3,4]. Given the current rate of climate change, the Food and Agriculture Organization (www.fao.org) predicts that by the next century, global production of main cereal crops will have decreased by as much as 45%. The rate of agricultural production must therefore be significantly increased in order to feed the world's hungry. For this reason, contemporary agriculture is severely limited in its ability to produce the resources needed to support climate change adaptation, support related trade, and produce bioenergy. By using crop genetic resources for chromosomal-mediated gene transfer (also known as "plant breeding") into contemporary genetic backdrops, novel technologies are undoubtedly assisting global agriculture in meeting consumer needs [5]. By incorporating economically significant features into crop plants, the development of contemporary genetic engineering, molecular breeding (marker-assisted selection), hybrid seed production, plant tissue culture, and genome editing techniques has further improved the current state of affairs [6]. Modern agriculture's primary goals are to increase net production per capita and decrease stress-induced annual losses through the use of cutting-edge biotechnology techniques.

A gradual transition from traditional agriculture, which relied on humans and animals, to automated, data-driven smart farming (agriculture revolution 4.0), which focuses on sustainability and climate resilience, addressing food security, resource conservation, biodiversity support, and climate change mitigation. Over the years, significant changes and innovations in agricultural practices and technology have increased food production, contributed to population growth, and induced social changes. Sustainable agriculture is essential to tackling today's and tomorrow's problems, such as feeding the world's expanding population while protecting natural resources and reducing climate change, all while ensuring the welfare of coming generations. By encouraging the prudent and effective use of water, soil, and energy, sustainable agriculture lessens the environmental impact of agriculture while simultaneously protecting the health and welfare of both farmers and consumers. In order to lessen pollution and slow down climate change, it specifically encourages improving soil carbon sequestration and lowering carbon emissions from livestock, encouraging the use of renewable energy sources on farms, and limiting the use of chemicals on crops, soils, and antibiotics and pharmaceuticals in animal husbandry.

Modern agriculture is greatly aided by emerging information and communication technologies (ICT), which make it possible to gather knowledge and insights from a large amount of diverse data to support well-informed decision-making. This optimizes agricultural-related activities, conserves resources, and eventually increases production yield in a sustainable and efficient manner. The development of sustainable and resilient farming practices is greatly aided by Next Generation Internet of Things (NG-IoT) technology, robotics, artificial intelligence (AI) methods, big data analytics, and data science, as well as remote sensing (both aerial and space). A collection of indicative enabled smart applications for sustainable agriculture, bolstered by data availability and advanced predictive capabilities, include soil and crop health [1], crop growth assessment [2], pest and disease detection [3], weed detection [4], mapping [5], environmental monitoring [6], livestock monitoring [7], and animals’ welfare assessment [8].

 The vast number of linked IoT devices and the volume and diversity of data produced from many sources provide a number of difficulties, such as data availability and reliability, data quality, latency, energy efficiency, security, privacy, scalability, and interoperability. It is anticipated that NG-IoT infrastructure will result in intelligent applications and well-informed decision-making based on vast amounts of real-time data that satisfy strict performance metrics (such as time-related constraints), while also accounting for network and computational resource limitations and protecting user and data security and privacy. In order to increase the acceptability of suggested solutions, applications, and services, people's faith in new technology developments should be strengthened. While preserving the soundness of the suggested solutions, transparency, interpretability, and explainability are crucial in this regard. Our study focuses on new ICT technologies that are essential to attaining sustainable agriculture. First, the state-of-the-art in enabling technologies is reviewed, emphasizing the difficulties and constraints. Proposed solutions are then discussed, taking into account data transmission and collection (including various data sources and networking technologies), big data ingestion and integration (including data storage, quality, interoperability, and security issues), and data analysis (including predictive analytics, AI, and ML techniques). The function of blockchain is also emphasized. We then highlight the importance of human-centered NG-IoT systems, robust and explainable AI, and Augmented Reality (AR) as a next step.

**Data Sources**

**Sensors**

 Sensors installed in a variety of habitats, including natural settings [20], agricultural fields [19], and controlled areas like greenhouses [21], are essential for the real-time measurement and transfer of data related to particular parameters of interest. Plant health indicators (such as the Normalized Vegetation Index (NDVI), which is obtained from sensors detecting plant reflectance, soil moisture levels, weather station data, and other water quality metrics like pH and conductivity are some examples of these factors. Furthermore, sensors that track the levels of nutrients (such as potassium, phosphorus, nitrates, etc.) have been essential to precision farming [22]. Additionally, incorporating nano-biosensors into applications for chemicals, water, and nutrients has the potential to significantly reduce manufacturing costs while simultaneously addressing environmental problems [23]. Generally speaking, sensors and associated data allow for precise control over the application of pesticides and fertilizers, optimize irrigation schedules, encourage the safe and effective reuse of treated wastewater, identify the best times to harvest crops, and establish the best growing conditions for agricultural products.

Additionally, to ensure the safety of drinking water in residential, commercial, and agricultural settings, routine water quality testing is essential. In laboratories, traditional techniques like qualitative analysis have been widely used to identify water characteristics and calculate the water quality index. However, when compared to modern instrumental analytical techniques, these approaches are known for being costly, time-consuming, and labor-intensive. Research is being focused on creating specialized sensors to improve accuracy and enable real-time measurements of relevant parameters in response to these difficulties. With special potential for agricultural applications like irrigation using treated wastewater, these sensors provide a workable substitute for the drawn-out procedures of conventional laboratory tests [24]. In the field of wildlife monitoring and animal husbandry, implanted biosensors and wearable collars with sensors have been useful for gathering information on the health and welfare of animals [25]. In addition to measuring vital signs like blood oxygen saturation, heart rate, and body temperature, these sensors can also predict when and how different activities like eating, drinking, and sleeping occur. For particular uses, they also provide identification systems that enable precise recognition of every animal [26]. Additionally, precise location data for both cars and animals is provided via the combination of Global Navigation Satellite Systems (GNSS) and Global Positioning System (GPS), which improves accuracy and minimizes resource waste [27].

**Unmanned Aerial Vehicles**

In precision agriculture, unmanned aerial vehicles (UAVs) are a crucial tool that help advance precision farming and promote sustainable farming methods. Their contribution is demonstrated by their use of cutting-edge technologies like artificial intelligence (AI) and machine learning (ML), as well as cloud and edge computing capabilities, to provide complex and data-driven insights regarding various important aspects of agriculture, such as crop health, soil conditions, and pest management. These insights allow for the remarkably accurate forecasting of agricultural patterns [9]. In the agriculture industry, this data-driven strategy enhances farming operations' accuracy and efficiency, enabling informed decision-making and resource optimization [10]. A wide range of UAVs, including single- and multi-rotor and fixed-wing aircraft, have been used in agricultural settings. These include cameras and sensors such as thermal, RGB, multi-spectral, and hyperspectral cameras [11]. A highly accurate and up-to-date perspective of the entire agricultural region is made possible by the efficient use of UAVs to create precise Digital Elevation Models (DEMs) and Ortho mosaic maps of agricultural fields [12]. This helps farmers identify trends and problems in their fields, and also reveals differences in the elevation of the terrain, which helps with drainage planning and soil conservation efforts. With the use of cutting-edge multispectral and hyperspectral sensors, UAVs can create accurate Vegetation Index Maps that include popular metrics like NDVI. With the help of this data-rich approach, crop health can be thoroughly assessed, and stressed or diseased plants can be identified with a high degree of accuracy [13]. Furthermore, UAVs are essential for evaluating crop health because they use their sophisticated imaging capabilities to reveal complex patterns of disease, stress, and nutrient deficiencies that may affect plants. Additionally, farmers benefit greatly from UAVs' ability to give them critical information about disease outbreaks and pest infestations in their fields [14]. Farmers can use this knowledge to create focused treatment plans that minimize the need for broad-spectrum chemical agents and maximize resource utilization, thereby encouraging ecologically friendly farming methods. Additionally, UAVs can provide crucial data about the characteristics of soil, such as its moisture content, texture, and organic matter content [38]. Farmers are equipped with the information they need to make wise decisions about fertilization, irrigation, and soil management thanks to this thorough soil data.

**Unmanned Ground Vehicles**

When it comes to agricultural technology, UGVs or agrobots have a great deal of promise to improve different facets of farming methods [15]. Precision agriculture can benefit greatly from the automation of chores, labor optimization that lowers costs, and the provision of vital data for well-informed decision-making that these autonomous or remotely operated ground-based vehicles offer. Equipped with a variety of sensors, cameras, and GPS technology, UGVs navigate agricultural fields with ease and autonomously collect vital information about soil conditions, crop health, and environmental factors. This information is then used to create detailed field maps and support informed, data-driven decisions for tasks like planting, irrigation, fertilization, harvesting, and pest control. The capacity of UGVs to perform a wide range of jobs precisely is one example of their versatility. For example, UGVs can routinely gather soil samples over large fields, offering important information about soil texture, pH balance, and nutrient levels. This information can help develop tailored nutrient management plans, which will lessen overfertilization and improve soil health overall [16]. Furthermore, UGVs equipped with specific mechanical or chemical weed management systems are able to maneuver skillfully inside crop rows, identifying and getting rid of weeds in a targeted way [17]. In a similar vein, these vehicles are excellent at applying pesticides precisely, focusing treatment on locations where pest infestations are present and reducing the need for broad-spectrum chemicals [18]. Furthermore, UGVs can be modified to become autonomous tractors that can work around the clock to plant, harvest, and plough crops without assistance from humans [62], [63]. Operating around the clock is encouraged by this autonomy, which greatly increases productivity and reduces personnel expenses. The harvesting process can be streamlined and labor-intensive tasks reduced in specialized agricultural settings like orchards and vineyards by equipping UGVs with specialized harvesting arms and sophisticated vision systems [19], [20], [21], [22], and [23]. This lessens the demand for physical work and improves safety by reducing the requirement for humans to perform repetitive or possibly dangerous tasks.

However, UGVs, who are frequently referred to as the "digital shepherds" of contemporary agriculture, go beyond crop-related applications to play crucial roles in effective and compassionate animal management techniques [24]. Their proficiency in distributing feed consistently, continuously checking on the health of the animals, and facilitating the movement of animals across pastures is invaluable. Furthermore, UGVs with environmental sensors are essential for gathering information on water quality [25] and soil erosion [26], enabling farmers to make environmentally sound choices about conservation and land management. While UGVs' reliable operation guarantees that agricultural tasks are carried out as accurately and efficiently as possible, flexible and customizable solutions are required to meet the unique needs and specifications of particular applications in various agricultural settings, improving sustainable farming practices.

**Earth Observation and Remote Sensing**

In order to investigate the dynamic systems of our globe, the science of EO integrates a variety of measurement techniques. In-situ data gathering, aerial surveys, and ground-based measurements are all included in these methods [27]. Examples of space agencies and organizations that work together on Earth observation include the National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric Administration (NOAA), the United States Geological Survey (USGS) for the United States of America (USA), and Copernicus for Europe. NASA is the leader in space and aeronautics, NOAA in weather and marine research, the USGS in geospatial mapping, and Copernicus in providing Earth observation data. In particular, remote sensing, a separate aspect of Earth observation, is concerned with gathering data by analyzing photographs taken by satellites or unmanned aerial vehicles [28]. Meanwhile, developments in remote sensing technologies and computing power have transformed data provisioning, improving temporal and spatial resolution and covering a wider range of spectral domains to monitor parameters such as soil [29], crops [30], and water quality [31] in a cost-effective and time-efficient way. The emphasis on using the sun spectrum's reflected light to learn more about vegetation conditions has also expanded at the same time. An further source of useful information in the optical and near-infrared spectrum is the fluorescence of chlorophyll in plant leaves, which offers vital information on vegetation productivity [32]. More frequent data updates are made possible by recent advancements in sensor technologies, data management, and data analytics. This increases the possibility of providing farmers and other agricultural stakeholders with reliable and financially viable information services, enabling data-driven decision-making, and offering practical advice on sustainable agricultural practices [33].

 There are several types of remote sensing, and each has a distinct function in the collection and analysis of data for precision farming. Measurement of natural electromagnetic radiation emitted or reflected by objects on the Earth's surface is known as passive remote sensing, and it is used for environmental monitoring [35] and land cover classification [34]. Because it makes it possible to map topography, assess soil moisture, and identify crop growth stages, active remote sensing especially via radar systems is essential to precision agriculture [36]. In order to monitor crop health, detect nutrient deficiencies, and evaluate soil qualities, multispectral remote sensing which uses sensors that record data at several wavelengths is essential [37]. Applications such as accurate crop disease diagnosis, in-depth soil nutrient analysis, and the identification of particular plant species are supported by the improved material identification capabilities provided by hyperspectral remote sensing [38]. Agricultural fields are monitored for temperature variations using thermal infrared remote sensing. It aids in determining irrigation requirements, evaluating crop stress, and maximizing water use [39]. Furthermore, precision agriculture benefits from the use of Light Detection and Ranging (LiDAR) technology for tasks like terrain modeling, elevation management, and topographic mapping. These tasks include precision irrigation, managing elevation differences in agricultural landscapes, and contour farming, which involves planting crops along a field's natural contours or elevation lines to minimize soil erosion [40]. Although technology has become more accessible and affordable, the agriculture industry has not yet fully adopted the use of remote sensing in real-world situations. Among the difficulties include a lack of knowledge about the effectiveness of this technology, the accessibility and instruction of decision-support tools, problems with data interoperability across different sources, and the persistent worry about data accuracy [41]. Economic considerations and the particulars of the problem are the basis for sensor selection; visible sensors are appropriate for specific applications, whereas hyperspectral sensors provide rich information at a higher cost. Each platform, including satellites, Unmanned Aerial Systems (UAS), and manned aircraft, has pros and cons when it comes to economic considerations in the collecting of remote sensing data [42]. Managing large data, overcoming cloud cover limitations, and refining machine learning algorithms to solve accuracy and quality issues are all ongoing difficulties.

**Open Data**

The use of open data in precision agriculture is consistent with the deliberate integration of publicly available datasets, which is a key element of the larger big data concept. Big data includes large and complicated datasets that may be difficult for conventional data processing techniques to handle due to its enormous volume, velocity, and variety. In this regard, open data is a useful tool for improving agricultural decision-making procedures.

 In the context of agriculture, "big data" refers to the enormous datasets produced by a variety of sources, including sensor networks, satellite photography, and meteorological stations. Precision agriculture leverages this abundance of data to improve decision-making by extracting insightful information about important facets of agricultural operations [28]. Large-scale meteorological datasets, like OpenWeather and Agri4Cast, provide weather forecasts that help farmers make well-informed decisions about planting, irrigation, and harvesting. Machine learning algorithm training also heavily relies on open data. Open image databases include a wide range of visual data and are sourced from government agencies, academic institutions, and cooperative projects (e.g. PlantDoc, PlantVillage, etc.) [27]. This imagery is used as a basis for training computer vision algorithms for applications including yield prediction, disease and cultivation identification, and crop monitoring. The development of strong machine learning models suited to agricultural requirements on a range of diverse cultivations is encouraged and accelerated by the open and collaborative nature of these datasets.

**Data Transmission**

In order to maximize throughput, minimize delay, and lower energy consumption and provide sustainable solutions, future networks must be naturally efficient. For IoT end devices with limited resources and network equipment placed in difficult settings with sporadic power supplies, this requirement is especially important [13]. Additional resource demands are placed on networks by the emergence of new applications like augmented reality, holomorphic communication, and five-sense communication, as well as mapping and localization for autonomous UAVs/UGVs. These networks need to minimize latency and energy consumption while supporting extremely high throughput, bandwidth, and wireless access points [14].

**Big Data Ingestions and Integration**

Data availability's time-space granularity has significantly increased thanks to new data formats and volumes. Big data refers to extremely huge amounts of data, which creates problems with data ingestion, storage, cleansing, analysis, retrieval, and updating in a timely, cost-effective, and safe way. Security, privacy, and incentives should all be in place in addition to ensuring data quality and integrity. Additionally, in order to facilitate data interchange and reuse among many apps, interoperability should be provided.

**Data Storage & Management**

One of the most crucial phases of data analysis is data management, which is essential to guaranteeing the accuracy and dependability of the data. Analyzing raw data can be challenging since it frequently has several flaws and inconsistencies. Out-of-range numbers, missing data points, noisy data, excessive information, and inconsistent formats or structures are some of these problems [16]. As a result, many processing methods, including data normalization, filtering, and management of missing values, have been widely employed [11]. In order to simplify storage and analysis, data normalization is an essential pre-processing step that entails arranging data into a consistent format to remove duplication and inconsistencies [18]. Numerous techniques have been put forth, including median absolute deviation, Z-score normalization, min-max normalizing, and pareto scaling [18]. Data filtering is the process of choosing and removing pertinent information from sizable datasets according to predetermined standards, improving data quality and lowering noise. Several techniques, including the ensemble filter and iterative portioning filter, have been developed [26]. In order to lessen the influence of incomplete data on analytic results, techniques like imputation or removal are used when addressing missing values, which is still another crucial component. The removal of an instance, the employment of a prediction model, the substitution of the mean, and the substitution of a global constant are some of the most popular methods for handling missing values [39]. Historical data and sensor readings gathered over time are a useful resource in both the smart water and agricultural sectors for a variety of applications, such as decision-making [115] and prediction [4]. However, because of environmental unpredictability and seasonality [31], human mistake, network miscommunication, sensor inaccuracy, and other variables, the collected datasets (historical and sensor data) often suffer from incompleteness, noise, and inconsistency [10]. Effective data filtering, standardization, and handling of missing values are critical to decision-making [12], decision-making [14] and reference [22].

**Computing Capabilities: Cloud to Edge Orchestration**

The enormous volume, data intensity, and computationally demanding systems of the NG-IoT present difficulties for traditional centralized designs and concepts. IoT depends on cloud computing solutions to process and analyze received data and to use predictive processes to solve complex problems because end devices have limited computation, energy, and storage capabilities. However, because of the great physical distance that separates IoT endpoints from massive data centers, cloud architecture sometimes causes intolerable communication delays. Furthermore, these methods raise security and privacy concerns, scalability problems, bottlenecks from central processing, and the bandwidth usage needed to move data [30]. Technologies for edge computing have surfaced as a potential remedy for the earlier issues. Edge servers seek to reduce the communication lags associated with cloud infrastructure by moving the cloud closer to end IoT devices [31]. Faster data processing and analysis are made possible by this close proximity, which lowers latency and improves the general responsiveness of IoT systems [32]. Although edge servers provide a quicker and more effective fix, it's crucial to remember that they have drawbacks of their own, chief among them being their constrained processing and storage capabilities [30]. As a result, they might occasionally fall short of meeting the diverse and stringent needs of IoT applications.

**Data Quality**

To improve decision-making, automate procedures, and boost overall efficiency, NG-IoT applications use a range of sensors and crowdsourcing to collect and analyze data, extract valuable insights, and apply the knowledge gained. Any IoT-based smart application's efficacy is largely dependent on the data that sensors collect. Low-quality sensor data may result in subpar recommendations since inaccurate or deceptive sensor data might undermine the validity of conclusions drawn from it, which will affect the overall efficacy of the application [41]. An Internet of Things application, for instance, can optimize field irrigation by utilizing data analysis from installed sensors (soil moisture, temperature, humidity, water level, and sun radiation) to ascertain the optimal watering schedule and quantity.

**Privacy and Data Protection: The Role of Blockchain**

As previously indicated, NG-IoT applications mainly depend on user input, which presents serious privacy issues. Because personal information, such as daily routines and activity patterns, could be readily revealed, security and privacy concerns are raised [5]. One of the biggest challenges is still striking a balance between protecting people's privacy and gathering useful data for analysis. Additionally, the increased danger of user identity and data leakage in traditional centralized systems exacerbates privacy and security concerns. A single point of failure is introduced by the centralized architecture, leaving the system open to possible data breaches. The use of blockchain technology, which increases transparency among participants and makes it easier to gather trustworthy data, can help address the problem of preserving data security and quality.

**Data Interoperability**

The sharing of data and outcomes between apps is restricted by the fact that each NG-IoT application is linked to its own platform, devices, application programming interfaces (APIs), and data formats [15]. The inability to create cross-platform and/or cross-domain IoT applications, the challenge of smoothly integrating non-interoperable IoT devices into different IoT platforms, and the eventual impediment to the broad adoption of IoT technology are all consequences of a lack of interoperability [17]. By integrating platforms from different domains and merging data from numerous platforms, cross-platform interoperability will make it possible to design new applications [18]. There are several benefits associated with NG-IoT based systems' support for data interchange.

**Data Analysis: Data Science and Artificial Intelligence**

By using historical data to make predictions about future events and utilizing statistical modeling, machine learning, and data mining, predictive analytics facilitates information extraction, trend observation, pattern recognition, and knowledge acquisition. These techniques offer insights to support well-informed decision-making in order to address important challenges. As seen in Fig. 1, some fundamental models for predictive analytics include time series analysis, classification methods, regression analysis, and clustering methods [16], [17]. Regression analysis specifically looks at how dependent and independent variables relate to one another. This method works especially well for forecasting continuous results from patterns in historical data. By using classification algorithms to forecast categorical results, data can be categorized into pre-established groups. Using clustering techniques, data points are grouped according to similarities, forming segments or clusters within the dataset. Last but not least, time series analysis is concerned with forecasting future values from historical observations in time-ordered data. In agriculture, time series analysis is very useful for forecasting weather patterns and crop yields. Neural networks, k-means, decision trees, and random forests are common algorithms linked to these models.

**Machine Learning / Deep Learning**

Artificial Intelligence (AI) refers to the ability of machines to simulate human cognitive processes in order to improve approaches to problem-solving. In a variety of applications, artificial intelligence (AI) is a key component driving the development of automated or semi-automatic decision support systems (DSS). Big data improvement is essential for operational process optimization and optimal decision-making [26]. The development of new technology and methods to increase the accuracy of data collection is ongoing. The use of advanced machine and deep learning algorithms as well as data fusion techniques into sensor data analysis is especially notable since it aims to provide more accurate and useful insights. These developments are crucial in promoting more sustainable and effective farming methods by improving the precision of irrigation [17], crop disease, and pest management [18] recommendations. Dominated by machine learning techniques, artificial intelligence (AI) uses mathematical methodology to draw conclusions from large datasets, understand complex structures on its own, and build reasoning systems without the need for explicit rules. Crop disease detection [12], [13], yield prediction [14], [15], soil mapping [17], soil nutrient prediction [18], water quality assessment [19], [10], and smart irrigation [11] are just a few of the precision agriculture applications where machine learning algorithms have demonstrated promise. The three main categories of these algorithms are reinforcement learning [21], unsupervised learning [20], and supervised learning [29]. In supervised learning, the model learns to map input properties to predetermined output labels by using labeled datasets to train the algorithms. Support Vector Machines (SVM) [22], Random Forest [13], and Convolutional Neural Networks (CNN), one of the most widely used neural network architectures, [14] are notable examples of methods in this area. Another well-liked supervised approach is regression modeling, which uses input information to predict numerical values.

**Conclusion**

In order to increase the efficiency and sustainability of the agricultural system, precision agriculture is a cutting-edge farming technique that integrates technology such as sensors, cloud computing, IoT, AI, ML, and automation. According to research, precision technologies have the ability to make big changes. For example, smart irrigation techniques can save 20% to 30% of water, and variable rate application techniques can reduce fertilizer usage by up to 15%. Similarly, in pilot tests, AI-based pest detection systems have demonstrated accuracy levels ranging from 85 to 95%. Although these figures demonstrate precision agriculture's potential, real benefits depend on factors including crop variety, local climate, infrastructure, and deployment size. Though their widespread adoption and impact on farm-level productivity need to be confirmed, future developments in technologies like 5G, edge computing, and blockchain may offer improved connectivity, faster data processing, and greater transparency in agricultural supply chains. With some field experiments claiming a 10% yield gain when integrated systems are employed, advancements in sensor technology and AI algorithms are expected to improve the accuracy of decision-support tools. Through the integration of these technologies with precise conservation techniques and climate-resilient methodologies, we can reduce environmental damage, promote food security, and ensure long-term sustainability. Resolving the issues of accessibility, ethics, and inclusion is crucial to maximizing the benefits of precision agriculture while ensuring that smallholder and marginalized farmers are not at a disadvantage as a result of the technological change.

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