

Artificial Intelligence in Sustainable Smart Agriculture: Concepts, Applications, and Challenges

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Abstract

Artificial Intelligence (AI) has emerged as a transformative force in modern agriculture, revolutionizing traditional farming practices into smart agriculture ecosystems. This paper presents the ideas and uses of AI in smart agriculture, therefore highlighting its great influence on improving farming efficiency, sustainability, and production. Based on a number of layers that facilitate data collection, data analysis, and decision-making, in the farming processes, we propose in this paper an AI-based Internet of Things (IoT) platform of smart agriculture. There are also other AI-based technologies such as Machine Learning (ML), computer vision, and IoT integration, explored in this paper, that can give farmers the ability to access real-time data, predictive analytics, and autonomous decision-making power. We also discuss the ways AI would address some significant agricultural challenges, such as optimisation of resources, climate resilience, insect control and monitoring of crops. The paper explains the promising future of smart farming based on AI in ensuring sustainable farming and food security in the world.

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1 Introduction

The 21st century is experiencing the radical revolution of agriculture as the ancient practice of growing crops and raising livestock is shifting towards a new era of technological advancement and creativity in agricultural practices



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[1, 2]. This transformation is predetermined by the integration of Artificial Intelligence (AI) into the agricultural industry, which creates so-called "smart agriculture" or "precision agriculture" as it is commonly described as such [3]. The terms smart agriculture and precision farming are used interchangeably in the literature, but represent different scopes: precision farming is a site-specific management process that relies on sensor data, satellite images, and mapping field variability to apply farm inputs (e.g., water, fertilizers, pesticides) to optimize yield efficiency at the micro level (e.g., fields, areas, or spots) [4, 5]. Contrarily, the idea of so-called smart agriculture can be seen as a new paradigm of food production, where practical experience and modern AI technologies intertwine to create an ecological, effective, and highly productive food production ecosystems [6, 7].

The world is experiencing unprecedented problems in the agricultural field. The population of the globe is estimated to reach up to 10 billion people by the year 2050 and thus the need of food, fiber and bioenergy is increasing exponentially as well [8]. At the same time, the new demands on agriculture systems are posed by the effects of climate change, depletion of resources, and the changes in weather patterns [9, 10]. In this respect, AI comes as a strong partner in overcoming such issues, suggesting creative solutions to enhance agricultural productivity, optimize resource utilization and reduce the environmental cost of issues [11, 12]. The paper provides a general overview of AI in smart agriculture, trying to grasp the basic ideas and various implementations. Our interest to do the investigation is driven by the fact that agriculture has always been considered as a traditional and labor intensive sector, which is at the brink of a technological revolution that could empower farmers and other stakeholders within the value chain.

The fundamental aspect of AI in agriculture is the ability to elicit relevant conclusions about large amounts of data. Farmers could make real-time data-driven decisions using smart sensors, data analytics, and Machine Learning (ML) algorithms based on the data they capture and process with the help of an artificial intelligence system (AI) that analyses and interprets the gathered data [13]. These decisions cover a wide range of tasks, including specifics of fertilization and timely irrigation to the condition of crops to the invasion of pests. Typically connected with drones and driverless cars, computer vision systems may enable farmers to monitor the situation on the fields in the perspective of the eye of the bird, detecting the sphere that needs care.

One of the most incredible benefits of AI in the field of agriculture is its adaptability and scalability. Starting with a smallholder farmer in an isolated town and then extending to a large agribusiness corporation with big farms, AI can be tailored to the specific needs of any other agriculture company. AI is impacting the agricultural industries in a wide fashion, including improved supply chains and increased agricultural productivity. In the article, we explore the plethora of how AI can be found in smart agriculture through actual examples, pictures, situations, and most recent research results. We are also discussing the issues related to data security, accessibility, and ethical use of technology in the agricultural industry and, therefore, cover the opportunities and concerns associated with the notorious use of AI in agriculture. Thus, AI in agriculture is bringing a new era of unprecedented innovation and transformation. The paper is a guidebook on the complex landscape of AI in smart agriculture, demonstrating the potential of this technology to promote food production and sustainability, efficiency, and even intimacy not only to the world population but to do so.

The important contributions of this article are as follows:

- An introductory knowledge of the principles of AI, preconditioning its use in the agricultural sector, is given.
- The most important AI technologies that are important to the agricultural transformation are discussed.
- Various uses of AI in the agricultural sector, such as precision crop management and autonomous farming are explored in depth.
- The critical AI-based Internet of Things (IoT) framework that has been supporting smart agriculture is described.
- There are a number of opportunities and challenges related to the adoption of AI in smart agriculture, which

is discussed with references to the challenges and potential of innovations.

- Potential developments and future perspectives of AI and how it can be applied in smart farming are discussed.

1.1 Review Methodology

In order to endorse the multi-dimensional purposes of this article, the descriptive and thematic literature review approach is used. The process of review was aimed at identifying, synthesizing, and critically analyzing recent and the high-impact studies in the field of AI applications in smart agriculture. Peer-reviewed journal articles and reliable conference proceedings published recently were searched systematically in scholarly databases, such as IEEE Xplore, SpringerLink, ScienceDirect, Elsevier, and Scopus. Keywords used through different combinations like: *AI; IoT; ML; precision farming; sustainable smart agriculture; and sustainable farming* were used as the search strategy. English only studies of technical richness as well as empirical validation and architectural insight were only retained to be analyzed thoroughly. The chosen literature was then planned according to the flow of the article. To begin with, the fundamentals of AI and technologies were discussed to create a theoretical background of agricultural integration (Section 2). It was preceded by a detailed discussion of AI application in different areas of agriculture, such as crop control, livestock, and soil control (Section 3). The second step involved the analysis and breaking down AI-enabled IoT architecture, which is regarded as the functional backbone of smart agriculture, into functional layers (Section 4). The review also went further to recognize the practical challenges i.e. data quality and interoperability as well as the possible opportunities of scalable deployment (Section 5). Lastly, to predict the future, new interdisciplinary trends and predictions of the intersection of AI and agriculture were examined and put into context (Section 6). This systematic approach to research guaranteed that both theoretical and practical aspects of the concept of AI in the agricultural industry were thoroughly covered with references to the key contributions of the article.

The organization of this article is structured as follows: Section starts by establishing a background in AI principles and moves on to discuss the most important AI technologies. In Section 3, Various AI uses ranging precision crop management to autonomous farming are discussed. Section 4 explores the AI-based IoT structure that is critical to this ecosystem, and then takes a short explanation of various layers. Section 5 solves the issue of AI adoption challenges and opportunities. Section 6 looks into the future, cutting across the growing trends and forecasts in AI and farming. Lastly, Section 7 provides the closing statements of the article.

2 AI concepts and their relevance to smart agriculture

This chapter is critical in offering a background information about the application of AI in agriculture. The purpose of this section is to provide the bibliophiles with the basic knowledge on the most important concepts of AI and its direct application to the field of agriculture. Figure 1 below, AI-concept, depicts the concepts and the underlying technologies of AI that apply to smart agriculture. The following section is discussed in detail:

2.1 Fundamental AI concepts

Here we will consider the basic concepts of AI and their implications to the area of agriculture. We shall explore the uses of ML [14-16], deep-learning[17], and Natural Language Processing (NLP) [18] in developing the foundation of AI integration in farm activities metamorphosis. Being aware of such concepts enables a person to comprehend better the AI-driven changes to the agricultural industry and consequently the rise of data-driven productivity and efficiency.

2.1.1 Machine Learning

It is an essential part of the agricultural revolution that is AI-powered. It involves the creation of mechanisms of computer programs to learn through the data and produce verdicts or forecasts without direct programming.

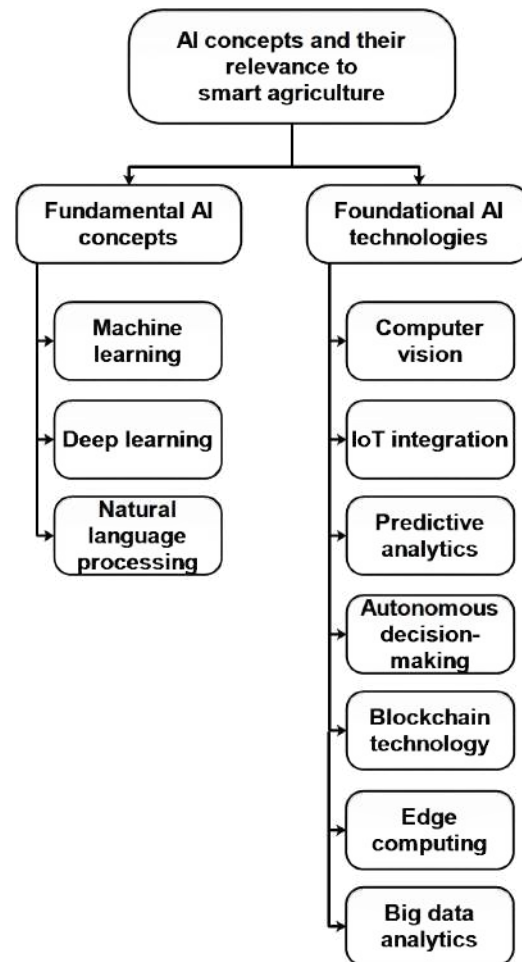


Figure 1. AI fundamental concepts and foundational technologies relevance to smart agriculture

ML could make a complete transformation in agriculture. It accurately predicts crop yields through historical information, such as weather, soil status, and farming habits, citing historical data, e.g. weather, soil status, and farming methods as examples, [19]. This information aids the agriculture sector to effectively manage resources and plan their harvest. In the early stages, photo analysis in ML is able to detect agricultural diseases or pest infestations, hence allowing timely intervention to be made possible [20, 21]. It also assists in optimizing resources by advising on optimal distribution of best resources i.e. pesticides, fertilizers and water using a variety of data sources. This boosts the quality of crops and prevents wastage of resources hence beneficial farming practices that are environmental friendly.

2.1.2 Deep learning

One of the branches of ML that are good at multidimensional pattern recognition is it. In farming, it is good at the activities that require picture analysis. Deep learning is a learning technique that employs the artificial neural networks (ANNs) and multiple layers to represent data as well as learn data at varying levels of abstraction. This ability would be very handy in agriculture to identify the image, because the deep learning models can detect particular diseases of crops or infestation of pests by analyzing the crop image. The timely identification would be essential to start timely crop protection. In monitoring plant growth, deep learning is applied to measure plant height, health of leaves, and growth rates through analyzing crop photos over time images of crops [22]. The information helps in determination of crop well being and growth so that farmers make decisions based on data.

2.1.3 Natural language processing

Although NLP is not traditionally associated with agriculture, it also plays a specific part in this industry. NLP is a field of AI, which deals with computer cooperation with human speech, enabling computers to interpret, read, and create language [23]. NLP can be used in the agricultural-industry, e.g., in market analysis whereby textual data can be provided from various sources for e.g. in the market reports, the news paper, social media and the software will analyze the data and then make better interpretation of the market trends, customer feelings, and the price trends. As an example, news articles can be processed in NLP to extract information that interferes with the prices of agricultural commodities, and this information can be used to be of great benefit to the farmers and traders. Also, NLP can facilitate knowledge sharing among the agricultural community because it becomes easier to comprehend and exchange agricultural knowledge and research. This would help to ensure that the professionals in various areas work together to a great deal and eventually promote the agricultural knowledge and practices.

2.2 Foundational AI technologies

Computer vision, IoT integration, predictive analytics, autonomous decision-making, blockchain technology, edge computing, and big data analytics are only some of the foundational AI technologies that are relevant in smart agriculture [24]. Essentially, these pioneering AI technologies are the foundations upon which the agricultural revolution is based, and a new era of farming that is smarter and more resilient, efficient and responsive to any global issue is becoming a reality. They empower farmers to have data-driven visions, automated decision-making, secure and traceable transactions, and real-time analysis, building a future where agriculture is not only more productive but more sustainable and flexible to the needs of the 21 st century in a manner that is traceable and secure in nature [25].

2.2.1 Computer vision

Computer vision is one of the groundbreaking AI technologies in the field of modern agriculture at the headline level[26]. The ability of machines to recognize and appreciate the visual world makes it its main strength that is transformative to farming, in particular. Computer vision allows agricultural systems to see and understand important details of crop health, field conditions, and others by the use of cameras, sensors, and advanced algorithms. This can translate to early detection of diseases, accurate crop growth, and detection of pest infestations with such accuracy. Image and video data analysis will result in real-time monitoring and decision-making, which will provide farmers with actionable information to enhance productivity and reduce losses. The use of computer vision brings agricultural sector into a new phase where the visual world is a potential source of a lot of information and knowledge, which improves all areas of farming.

2.2.2 IoT integration

Through IoT integration, modernization of agriculture is important as the devices, sensors, and equipment in the farming economy are interconnected [11]. This interconnection will transform conventional farms into smart systems that are interconnected so that there is a smooth flow of communication and data exchange. Different parameters are monitored by sensors, such as weather, soil moisture, equipment operation and livestock well-being, whereby the data is gathered, processed, and shared in real-time. This is a real time exchange of information that helps farmers to make good decisions that improve their efficiency and sustainability. An example is that, linked irrigation systems have the potential to adjust the water supply based on minute weather predictions and physical properties in order to use resources efficiently and ensure crop well-being. IoT integration assists farmers to have the full picture of their activities and hence advance improved and more connected farming techniques.

2.2.3 Predictive analytics

Having a history and real-time information predictive analytics to forecast future trends and outcomes [27] is one of the pillars of data-driven agriculture. The complex algorithms are used to predict and pattern recognition. Predictive analytics is also evident in the agricultural field in the form of the ability to predict such key variables as crop growth, pest infestation, and planting periods. This forecasting capacity can help farmers to minimize risks and make proactive decisions. Farmers can predict the best planting window, therefore lowering the vulnerability of their crops to bad weather, by investigating past weather patterns and current soil data. Predictive analytics gives farmers the capacity to keep ahead of difficulties and make data-informed decisions, optimizing agricultural output and resilience.

2.2.4 Autonomous decision-making

Autonomous decision-making is a pillar of AI in agriculture that enables smart decisions to be made within the farming operations [28]. This technology relies on a combination of smart algorithms, real-time data processing, and ML to produce judgments that are not affected by human input. It is very efficient in scenarios where a quick response is required such as limiting the transmission of agricultural diseases or maximizing the irrigation. An example is the autonomous systems which are able to analyze information of various sensors to determine the precise when to initiate irrigation and thus optimize on the soil moisture levels. This enhances the health of the crops and also conserves valuable water resources and thus not only revolutionizes agriculture but also makes it more sustainable.

2.2.5 Blockchain technology

Blockchain technology gets its name in the agricultural industry by availing a safe, secured, and immutable record of transactions [29]. This technology is particularly useful in supply chain management in ensuring that agricultural products can be traced clearly to the source to the final customer. It generates clear and incorruptible registries, which ensures accountability of agricultural goods, which is a crucial attribute during food safety or quality issues. Detailed data on the origin and excursion of goods can be availed to the consumers and accountability and dependence in the food supply chain will be achieved. Blockchain makes agriculture a more responsible and transparent sector.

2.2.6 Edge computing

Edge computing reduces latency and enables real-time analysis by getting the computation of data as close to the source as possible. In farming, where one may need to make quick decisions, edge computing enhances the experience of the devices and sensors involved. It enables on-site processing of data, enhancing such essential programs as autonomous machinery and real-time observation of the situation on the field. Edge computing eliminates the necessity to transmit data to remote data centers to be processed, and thus the responses are fast, and smart agriculture is done its way best way to do it[30].

2.2.7 Big data analytics

The contemporary agricultural world is overwhelmed with numerous pieces of information provided by different sources and requires the use of big data analytics. It is this technology that serves as the engine which drives the process of mining valuable insights on this data deluge. It consumes and analyses different types of data such as historical data, sensor data and satellite images. The Big data analytics helps to make important agricultural choices by identifying trends and patterns to make decisions about resource allocation, relationship of crops and so on. This is the technology that can be used to enhance productivity and sustainability of farming practices. It

enables farmers to utilize the gem of data in their possession so as to make sound and strategic decisions, ensuring the sustainability of agriculture continues to exist[31]. The analysis of the concepts of AI and their application to smart agriculture in terms of strengths, limitations, and gaps in the research is critical and noted in Table 1 and emphasized.

Table 1. Critical analysis of AI concepts and their relevance to smart agriculture

Technology	Strengths	Limitations	Research Gaps
ML	Accurate predictions based on historical and sensor data; adaptable models.	Performance heavily depends on data quality and quantity.	Lack of generalization across different crops, regions, and climates.
Deep Learning	Excels at image classification for disease detection and phenotyping.	Requires large labeled datasets and high computational power.	Limited explainability; not well-integrated with physical models of plant growth.
Natural Language Processing (NLP)	Enables text mining from reports, market analysis, and weather alerts.	Domain-specific vocabulary and multilingual issues reduce accuracy.	Underexplored in rural advisory systems and low-resource languages.
Computer Vision	Enables real-time crop monitoring and early disease detection.	Affected by lighting conditions, occlusion, and image quality.	Integration with multispectral and drone imagery remains limited.
IoT Integration	Real-time sensing and monitoring of the environment, soil, and crops.	Connectivity issues in remote areas, and sensor calibration complexity.	Interoperability across devices and platforms still challenging.
Predictive Analytics	Forecasting crop yield, pest outbreaks, and optimal planting schedules.	Sensitive to data noise and seasonal anomalies.	Requires context-aware models for better decision-making.
Autonomous Decision-Making	Enables real-time automated actions (e.g., irrigation, pesticide spraying).	Dependence on real-time accurate data; limited adaptability.	Needs robust fail-safe mechanisms for edge-case scenarios.
Blockchain Technology	Enhances transparency and traceability in food supply chains.	High energy cost and scalability concerns.	Integration with AI-driven traceability tools is still immature.
Edge Computing	Reduces latency for time-sensitive agricultural operations.	Limited computational power and storage at edge nodes.	Optimal balance between edge and cloud remains underexplored.
Big Data Analytics	Unlocks insights from vast multi-source agricultural datasets.	High complexity in cleaning, integrating, and interpreting data.	Need for domain-specific big data pipelines tailored to agriculture.

3 AI applications in smart agriculture

This section gives a detailed research on the application of AI in transforming agriculture to result in more efficient, productive, and sustainable farming. And we explore different AI-based applications in different fields of agriculture, such as crop management and livestock monitoring, and soil analysis. The classifications of AI applications in smart agriculture are depicted in Figure 2. [24, 32, 33].

3.1 Crop management

It is a sad attribute of the modern agricultural practice that it is managed by crops, and AI has a highly significant impact on its improvement, starting at planting and ending at harvest. The following are the key AI applications under this category:

3.1.1 Precision agriculture

Also commonly known as smart farming, precision agriculture is a disruptive technology of crop management leveraging AI and data-oriented technologies to achieve high productivity, but with minimal resource usage. AI is engaged in a number of ways:

(1) Data-driven decision-making: AI works with an enormous amount of information collected through multiple devices (drones, satellites, and ground sensors), to offer real-time data regarding the state of crops and soil. This will enable farmers to make evidence-based choices relating to pest management, fertilizer, and irrigation to allocate resources in areas and at the right time of need [34, 35].

(2) Variable Rate Technology (VRT): AI-based VRT technologies automatically reallocate the rate of input application (e.g., fertilizers, pesticides) using real-time information, which leads to the conservation of cost and

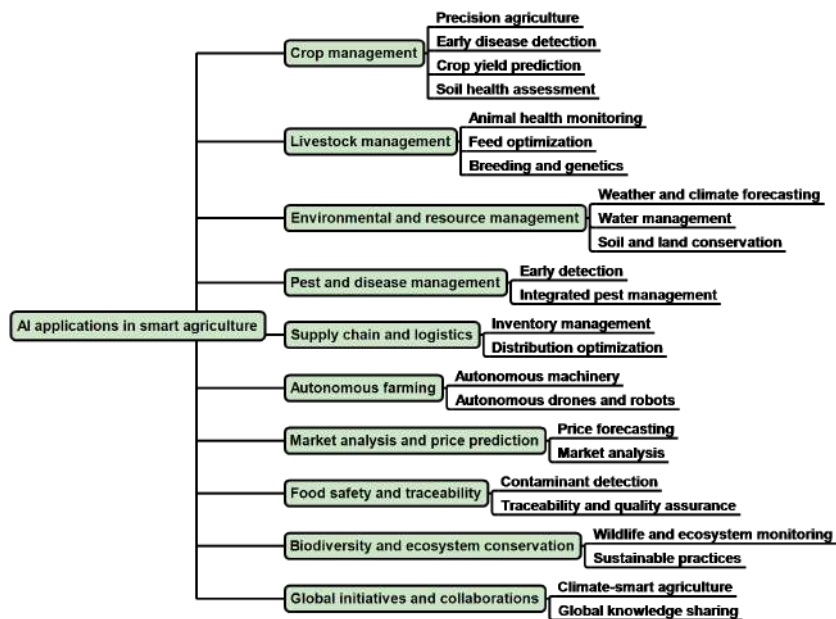


Figure 2. Classifications of AI applications in smart agriculture

environment-friendly services. The technology also allows the efficient utilization of resources, reducing wastage and making the agricultural practices more sustainable [36].

(3) Crop monitoring: AI-equipped drones with cameras and sensors provide detailed pictures of the fields. ML algorithms are used to identify issues such as weed infestations, lack of nutrition, and disease outbreaks using these photos. This allows the process of early intervention and treatment and enhances the healthy crops and yield in the end [37, 38]. .

3.1.2 Early disease detection

The significant risks to crop health are disease outbreaks. Their spread can only be averted through early detection. The benefits of early-disease detection systems on artificial intelligence include:

(1) Image recognition: AI is used to scan the photos of crops with markers of an infection using computer vision and image recognition methods. These pictures can be acquired using cameras, drones, or other sensors. AI can facilitate timely response to the signs of illness and minimize the transmission by early detection of its symptoms and subsequently preventing the infection from spreading further in time [39, 40].

(2) Predictive models: AI-based predictive models may be based on past data and current situations. The exploration of such factors as weather, soil type, and the type of crop will assist a person in predicting the danger of diseases and, therefore, to advise farmers on the necessary precaution. This proactive approach is important in ensuring crop quality and high yield [41, 42].

3.1.3 Crop yield prediction

Correct forecasting of crops is required in resource allocation, market planning and general farms management. AI develops this sphere in the following aspects:

(1) ML models: AI models, particularly ML algorithms, deploy the previous data about the crop performance, weather conditions, and soil conditions, as well as methods applied to farms, to forecast the yield in the current season. This information guides the decisions on resource use, planting, and harvesting decisions [34, 43].

(2) Real-time monitoring: Combining IoT sensors with AI yields IoT sensors in combination with AI also provide real-time information on crop conditions. With the data analysis, AI can adjust yield forecasts when the conditions vary in order to help farmers respond to unexpected challenges. This flexibility is necessary to maximize productivity when there is variability in the environment [43].

3.1.4 Soil health assessment

The health of the soil is the basis of crop development and sustainability. The methods of AI in supporting soil health include:

(1) IoT soil sensors: IoT connected soil sensors are used to monitor nutrients in soils, pH and moisture among others. This data is processed by AI, which recommends recommendations on how to manage the soil and amend it to maximize growth of plants [44]

(2) Predictive soil management: AI predictive models research past data and the surrounding environment to offer solutions on how to sustain soil health. It predicts the potential soil erosion and trains farmers on preventive mechanisms, therefore, ensuring long-term sustainable agriculture [44].

In essence, the AIs in crop management bring unparalleled accuracy, efficiency and sustainability to the agricultural re-harvests. It can enable the farmers with information based knowledge and real time information, which would result in increased yields, less wastage of resources and an ecologically viable way of farming. An example of how technology advances in the sphere of AI are shaping the future of food production is such technology integration.

3.2 Livestock management

Livestock management can be defined as a subdivision of agriculture that requires the care, well being and productivity of animals. AI technologies are crucial in improving the livestock productivity and well-being. The major applications of AI in this category are:

3.2.1 Animal health monitoring

The health of livestock is the paramount aspect of animal welfare as well as profitability of the farm. AI aids in animal health monitoring through various means:

(1) IoT sensors: IoT sensors are placed on animals to collect data on their vital signs, movements, and behaviors. AI processes this real-time data to detect deviations from normal patterns, which can be indicative of illness or distress [45, 46].

(2) Predictive analytics: Predictive methods driven by AI search for environmental conditions, genetic elements, and historical health records. AI can forecast health problems before they become serious by means of real-time health data comparison, therefore enabling farmers to act quickly to offer suitable treatment [45, 46].

(3) Disease recognition: By means of picture or sensor data, AI may identify indicators of common animal diseases. Cameras in animal housing areas can capture images of animals, and AI-powered computer vision may spot indications of diseases, including foot-and-mouth or mastitis [45, 46].

3.2.2 Feed Optimization

Good development in cattle and low costs depend on efficient feeding. AI facilitates the following kind of feed optimization:

(1) ML models: AI models consider elements including animal age, weight, and health, as well as nutritional requirements, in order to design perfect feed compositions. This ensures animals receive the right diet and helps to reduce feed waste [45, 46].

(2) Real-time monitoring: AI can follow animal eating patterns using cameras and sensors. AI can alert farmers about possible health concerns or feeding problems should deviations from normal eating habits be discovered, therefore enabling fast reactions [45, 46].

3.2.3 Breeding and genetics

The amalgamation of AI and genomics is increasingly becoming pertinent to improving livestock quality and productivity. AI allows more profound understanding of genetic patterns, prediction of traits, and optimization of breeding based on the large-scale genomic datasets.

(1) Genetic selection: Genetic selection AI, in particular, ML and deep learning models, can be applied to genome-wide association studies (GWAS) data to determine which markers are associated with desirable traits, including feed efficiency, disease resistance, and growth rates. This enables better genomic estimated breeding values (GEBVs), which enables the selection of better animals at earlier ages [45, 46].

(2) In Vitro Fertilization (IVF): AI algorithms combine sequencing, epigenetic, and heritability of traits based on genetic compatibility between parent lines. This facilitates the choice of the best sperm- egg combinations to increase the success of IVF and genomic diversity worth conserving [45, 46].

(3) Embryo selection: AI-powered models that have been trained on high-resolution embryo images and multi-omics data (genomic, transcriptomic) are used to predict an implantation success. Those are developmental potential assessments and chromosomal anomaly screenings that facilitate the process of selecting embryos with the greatest viability and genetic fitness [45, 46].

(4) Integrative phenomics: AI can also be used to analyse the phenomic data, that is, to connect the observed phenotype (e.g., body mass, milk yield) with the genome data through the neural networks. This integration improves trait prediction accuracy, especially under variable environmental conditions, and allows for robust genotype-phenotype mapping [186].

By combining AI with genomics and phenomics, Livestock breeding is becoming a new form of precision breeding as AI + genomics + phenomics will reduce the generation intervals and enhance the long-term productivity and resilience of animal agriculture.

3.3 Environmental and resource management

Environmental and resource management in agriculture is crucial for ensuring the sustainability of farming practices and the responsible use of natural resources. AI technologies have an important role to play in this aspect. This category includes the Weather and climate are fundamental factors that influence agricultural outcomes. AI contributes to weather and climate forecasting in the following ways:

3.3.1 Weather and climate forecasting

Weather and climate are fundamental factors that influence agricultural outcomes. AI contributes to weather and climate forecasting in the following ways:

(1) ML models: AI can use past weather patterns, the current weather, and world climatic patterns to provide correct short-term and long-term projections. This will help farmers to schedule their activities such as ploughing and reaping depending on the weather forecasts which are predictable and reliable to the farmers [47].

(2) Extreme event prediction: AI models have the ability to forecast life threatening weather conditions such as heat waves, floods and droughts, much earlier. This will allow farmers to perform precautionary measures to protect crops and animals [47, 48].

(3) Climate change analysis: AI is applicable to study long-term climate data, which helps to understand the trends of climate change. This information enables the farmers and policymakers to make effective decisions concerning the sustainable agricultural activities [47, 48].

3.3.2 Water management

Water management of agricultural products is important where there is water shortage to ensure the process is sustainable. AI helps in the management of water as follows:

(1) IoT sensors: Sensors are devices that allow real-time monitoring of soil moisture and water consumption. This information is processed by AI to provide certain irrigation approvals, which raise water consumption and reduce wastefulness [49, 50].

(2) Drip irrigation optimization: Drip irrigation optimization: AI is used to regulate drip irrigation systems, which ensures that crops receive the correct amount of water at the correct time. This saves water and helps in preventing over-irrigation [49, 50].

(3) Drought prediction: Predictive algorithms based on AI analyzing historical soil and weather data are used to forecast droughts. Early warning will enable the farmers to make informed choices and reduce the effects of drought on their crops [49, 50].

3.3.3 Soil and land conservation

Sustainable agriculture needs to preserve soil and prevent land degradation. AI can be used in conserving soil and land by:

(1) Soil health assessment: AI, as well as IoT sensors, evaluates soil health by measuring nutrient content, pH, and other characteristics. It gives advice on soil management activities to ensure fertility and avoid erosion [49, 50].

(2) Erosion prediction: Predictive models are based on topography and climate data with land use to extrapolate soil erosion risks. This knowledge directs land use development and conservation strategies meant to stop soil loss [49, 50].

(3) Land use optimization: Through analysis of elements such as crop rotation, cover cropping, and conservation strategies, AI aids in optimal land use techniques. These methods help to improve soil health and lower soil corrosion [49, 50].

3.4 Pest and disease management

Since numerous dangers affect the health and output of crops and animals, pest and disease control is a key focus of agriculture. Integrated pest control and early detection both depend significantly on AI technologies. The following key applications of AI are included in this part:

3.4.1 Early detection

Stopping the spread of pests and diseases and minimizing their impact on agricultural productivity depends on first discovering them. AI employs the following strategies to assist in early detection:

(1) Image recognition: AI probes photographs of crops, animals, or stored goods using computer vision and image recognition techniques. One can obtain these pictures with cameras, drones, or other sensors. AI can quickly spot indications of illnesses, insect infestations, or other anomalies not readily seen to the naked eye [51, 52].

(2) IoT sensors: IoT sensors positioned in storage spaces or on the fields can identify environmental changes linked with illnesses and pests. Using data from these sensors, AI detects anomalies, including unexpected temperature or humidity swings that can indicate the presence of pests or diseases [51, 52].

(3) Genomic analysis: When the pathogen or pest's identity is unknown, AI can examine genetic data to pinpoint the particular bug or disease causing the damage. This can guide farmers to definite and effective countermeasures [51, 52].

3.4.2 Integrated pest management

Integrated pest management (IPM) refers to a comprehensive strategy of controlling pests, encompassing a number of strategies. AI is beneficial to IPM in a number of aspects:

(1) Data integration: The combination of data on multiple factors, such as weather data, pest lifecycle information, and the history of pest infestation, will help AI to develop comprehensive models predicting the timing and location of pest issues arising in the future [51, 52].

(2) Decision support systems: AI-based decision support systems provide farmers with recommendations concerning pest and disease control. Such systems take into consideration a good number of factors, such as the life stage of the crop, weather condition, and life cycle of pests. As to pest control, the farmers will be able to make an informed decision on using pesticides or letting the natural predators loose human. In relation to pest control, farmers will be able to make an informed choice between using pesticides or letting the natural predators free [51, 52].

(3) Precision application: AI enhances the accuracy of approaches to pest management. As an example, it can control the discharge of advantageous insects in specific locations and time to focus on the pests, hence causing fewer harm to other species [51, 52].

(4) Real-time monitoring: IoT sensors and remote sensing technologies, in combination with AI, provide real-time monitoring of the insect populations. This knowledge is useful because it assists farmers to do what they are supposed to do when the number of pests reaches a level of threshold [51, 52].

All things considered, AI is essential for disease and pest control in agriculture since it provides first exposure via IoT sensors, image recognition, and genetic study. Moreover, by aggregating data from many sources, offering decision support, and allowing exact execution of control actions, AI helps integrate pest management. Protecting crops and animals as well as lessening the environmental impact of efforts at pest and disease management, depend critically on these uses. More efficient and sustainable, AI technology is changing the way agricultural pests and diseases are managed.

3.5 Supply chain and logistics

Competent supply chains and logistics management are crucial for agricultural products to reach customers in a timely and cost-effective manner. Simplification of these processes depends on AI technologies. The following main AI uses fall under this category:

3.5.1 Inventory management

Good inventory control guarantees appropriate tracking and storage of agricultural products, therefore reducing waste and expenses. AI helps with inventory control via the following channels:

(1) Predictive demand forecasting: Using previous sales data, market patterns, and other factors, AI projects future agricultural product demand. This data helps to keep ideal inventory levels and prevents understocking or overstocking [50, 53].

(2) Real-time monitoring: IoT sensors and data analytics track temperature and humidity, among other aspects of stored goods' condition. If circumstances stray from approved ranges, AI can send alarms to assist in stopping damage or spoiling [50, 53, 54].

(3) Supply chain visibility: From manufacture to distribution, AI provides a real-time supply chain view. This guarantees timely delivery, helps to track product movements, and forecasts delays [50, 53].

3.5.2 Distribution optimization

By means of better distribution of agricultural products, one can lower transportation costs and increase delivery efficiency. AI helps to optimize distribution by methods of the following:

(1) Route planning: To choose the most effective paths for delivering agricultural products, AI systems can probe elements including traffic conditions, weather, and supply chains. This lowers delivery times and fuel consumption [55, 56].

(2) Fleet management: AI helps in fleet management and optimization for vehicles utilized in product movement. It may track vehicle condition, plan repairs, and guarantee that the correct vehicles—for particular kinds of products—are employed [57, 58].

(3) Last-mile delivery: Last-mile delivery systems driven by AI help to increase the effectiveness of getting goods to end users. This includes maximizing delivery paths and applying drones or autonomous delivery cars [59, 60].

3.6 Autonomous farming

Autonomous farming is the application of AI-driven technologies to let robots, drones, and machinery do different jobs on the farm without direct human involvement. Among the main AI applications in this category are as under:

3.6.1 Autonomous machinery

AI-driven technologies seen in autonomous machinery like tractors and harvesters help to complete jobs, including planting, plowing, and harvesting. AI is involved as follows:

(1) Sensors and computer vision: Sensors and computer vision systems built into autonomous equipment allow it to negotiate fields, identify obstacles, and complete precise tasks free from human interaction [61, 62].

(2) Real-time data analysis: Data from many sensors is processed by AI to guide decisions on things like seed planting, soil condition, and plant health. More efficient and focused agricultural methods follow from this [61, 63].

Remote monitoring: Mobile apps and platforms let farmers remotely monitor and operate autonomous machinery. AI technologies guarantee that the equipment is running as expected and with efficiency [64, 65].

3.6.2 Autonomous drones and robots

On the farm, autonomous drones and robots handle a range of chores, including animal management and crop monitoring. Their operations depend much on AI.

(1) Crop scouting: Equipped with cameras and AI-powered image recognition software, drones may search fields for indicators of nutritional shortages, sickness, and insect pests. This information supports early intervention [66, 67].

(2) Weed control: Without herbicides, autonomous robots can prowl fields using AI to identify and eradicate weeds. This advances ecologically friendly farming [68, 69].

(3) Livestock monitoring: Sensible drones and robots can track animal movement, behavior, and condition. Using this information, AI finds problems and enhances animal well-being [70, 71].

Through inventory control and distribution optimization, AI is essentially changing supply chain and logistics management in agriculture. It simplifies product delivery and improves inventory control, therefore lowering waste and expenses. By means of autonomous machinery, drones, and robots, which enhance efficiency, precision, and sustainability in agriculture, AI is also transforming farming methods. These programs help to guarantee that farming methods are more environmentally friendly and efficient, as well as that agricultural products find consumers quickly.

3.7 Market analysis and price prediction

An agricultural company critically depends on market analysis and price prediction so that stakeholders and farmers may make wise decisions and adapt with the times. Optimizing these processes depends much on AI technologies. This section comprises the following main AI uses:

3.7.1 Price forecasting

In agriculture, price forecasting is the projection of future agricultural product prices depending on historical data, the state of the market, and several other elements. AI helps with price prediction employing the following approaches:

(1) ML models: To provide price forecasts, AI searches historical price data, supply and demand dynamics, weather conditions, and other factors using ML algorithms. These projections provide farmers and agribusinesses with worthwhile perspectives to guide pricing and sales decisions [72, 73].

(2) Market sentiment analysis: Using news, social media, and market data, AI can evaluate market sentiment and project price changes. Analyzing the emotions of market players helps one to get early warning signals of possible price movements [74, 75].

(3) Global market integration: By processing data from worldwide agricultural markets and commodity exchanges, AI can reveal how local prices could be influenced by foreign events [76, 77].

3.7.2 Market analysis

Market analysis is the study of agricultural market dynamics, including supply and demand, consumer preferences, and market trends. AI adds to market analysis in the following ways:

(1) Data integration: To offer a whole picture of the market, AI systems combine data from several sources—government publications, market polls, social media, and so forth. This information might cover consumer preferences, new product trends, and developing market sectors [78, 79].

(2) Consumer behavior analysis: By means of consumer behavior pattern analysis, AI can spot preferences and trends. This data enables agribusinesses and farmers to modify their marketing and production plans to meet customer needs [80, 81].

(3) Competitive analysis: AI can offer understanding of rivals' tactics and activity in the market. This lets companies decide with knowledge on marketing, pricing, and product development [82, 83].

(4) Market entry and expansion strategies: Whether local or worldwide, AI can help find fresh market prospects and create plans for entering or growing into new markets [84, 85].

All things considered, AI is quite important for agricultural market research and price forecasting. By means of insightful analysis of future pricing trends, price forecasting helps farmers and agribusinesses make wise decisions on output and sales. By means of market analysis, stakeholders can acclimate themselves to evolving market conditions and customer preferences by better understanding the dynamics of the agriculture market, consumer behavior, and competitiveness. By offering pragmatic insights and improving decision-making capacity, AI technology is changing the landscape of the agriculture industry.

3.8 Food safety and traceability

Maintaining consumer protection and the integrity of agricultural products along the supply chain depends on verifying food safety and traceability. These important factors are heavily influenced by AI technologies. This section comprises the following main AI uses:

3.8.1 Contaminant detection

Contaminant detection involves identifying and mitigating potential hazards in agricultural products, such as pathogens, pesticides, and contaminants. AI contributes to contaminant detection through the following methods:

(1) Image recognition: AI employs computer vision and image recognition techniques to analyze images of agricultural products, such as fruits, vegetables, and meat. It can identify visual signs of contaminants or abnormalities, like mold, discoloration, or foreign objects [86, 87].

(2) Spectroscopy: AI combines with spectroscopy techniques, such as near-infrared and hyperspectral imaging, to analyze the chemical composition of food products. By comparing the spectral signatures of products with known contaminant profiles, AI can detect the presence of contaminants [88, 89].

(3) Blockchain and IoT: AI systems integrated with blockchain and IoT technologies enable end-to-end traceability of food products. Any contamination event can be rapidly traced back to its source, allowing for timely recalls and investigations [90, 91].

3.8.2 Traceability and quality assurance

Traceability and quality assurance involve tracking the foundation and journey of agricultural products, confirming transparency, and maintaining quality standards. AI contributes to traceability and quality assurance through the following means:

(1) Blockchain technology: AI, combined with blockchain technology, creates transparent and immutable records of each step in the supply chain. This confirms that the origin, production, and handling of food products are easily traceable, providing consumers with confidence in product quality and safety [92, 93].

(2) IoT sensors: IoT sensors placed in shipping containers and storage facilities can monitor conditions such as temperature, humidity, and exposure to light. AI processes data from these sensors to ensure that products are stored and transported within prescribed quality standards [94, 95].

(3) Quality grading: AI can assess the quality of agricultural products based on various factors, including appearance, size, and nutritional content. This ensures that only products meeting quality standards are sold to consumers [96, 97].

(4) Food authentication: AI can verify product origins, therefore combating food fraud and counterfeiting. In high-value goods like premium wines or organic food, this is especially crucial [98, 99].

Food safety and traceability in agriculture depend on AI overall quite heavily. While traceability and quality assurance give openness and standards through the supply chain, contaminant detection guarantees that agricultural products are free of dangerous elements. Maintaining consumer health, guaranteeing product quality, and preserving faith in the agricultural sector all depend on these tools. By offering dependable, clear, and effective solutions, AI technology is reshaping food safety and traceability.

3.9 Biodiversity and ecosystem conservation

Maintaining the viability and health of agriculture depends on preserving ecosystems and biodiversity. Monitoring ecosystems and species, as well as encouraging sustainable practices, depends much on AI technologies. Among the main AI applications in this category are the following:

3.9.1 Wildlife and ecosystem monitoring

Monitoring ecosystems and wildlife helps one to better grasp how agricultural operations affect the surroundings and biodiversity. By use of the following approaches, AI supports monitoring of ecosystems and wildlife:

(1) Camera traps: Deployed in natural environments, AI-powered camera traps record photographs and recordings of animals. ML techniques search these images to identify species, count numbers, and track animal behavior [100, 101].

(2) Acoustic monitoring: AI can listen to audio recordings to find and name sounds produced by animals. Monitoring birds, frogs, and other vocal species especially benefits from this [102, 103].

(3) Satellite and drone imaging: Variations in land cover, vegetation health, and water bodies are assessed by means of satellite and drone photos explored using AI. These pictures support tracking of habitat changes and conservation initiatives. [104, 105].

(4) Real-time environmental sensors: IoT sensors are placed in ecosystems to collect data on environmental conditions, like humidity, temperature, and water quality. AI processes this data to monitor ecosystem health and detect anomalies [106, 107].

3.9.2 Sustainable practices

Promoting sustainable agriculture practices is essential for reducing the environmental impact and conserving ecosystems. AI is a powerful tool for biodiversity and ecosystem conservation in agriculture. It aids in monitoring wildlife and ecosystems, providing insights into the impact of agricultural activities and guiding conservation efforts. Additionally, AI stimulates ecological observations that decrease environmental damage and support the coexistence of agriculture and ecosystems. These applications are essential for maintaining biodiversity, ecosystem health, and the long-term sustainability of agriculture. AI technology is shaping the future of agriculture by aligning it with responsible and eco-friendly practices. AI contributes to sustainable practices through the following means:

(1) Precision agriculture: AI-driven precision agriculture optimizes resource use, reducing waste and minimizing the impact on ecosystems. By allowing particular application of water, pesticides, and fertilizers, it reduces contamination and overuse of resources [108].

(2) Conservation tillage: AI models help in determining optimal conservation tillage practices, which reduce soil erosion, maintain soil health, and conserve water [109].

(3) Crop rotation and diversification: AI can provide recommendations for crop rotation and diversification, which enhance soil health and reduce the reliance on chemical inputs [110, 111].

(4) Land use planning: AI is employed in land use planning to minimize the conversion of natural habitats into farmland, thus preserving critical ecosystems and biodiversity [112].

3.10 Global initiatives and collaborations

Collaboration on a global scale is essential for addressing the composite challenges facing agriculture, from food security to climate change. AI technologies play a pivotal role in supporting global initiatives and facilitating knowledge sharing. This category includes the following key AI applications:

3.10.1 Climate-smart agriculture

Aiming to both adapt to and lessen the effects of climate change and guarantee a sustainable food supply, climate-smart agriculture is a way forward. Employing the following approaches, AI supports climate-friendly agriculture:

(1) Climate data analysis: By means of historical climate data and real-time information, AI develops models for comprehending and predicting risk prediction about climate. This data guides legislators and farmers in their decisions on adjusting to new environmental conditions [113].

(2) Climate-resilient crop varieties: AI can identify drought-tolerant crops as well as other crop varieties more resistant to severe conditions. These kinds are essential for preserving food security, considering climate change [114].

(3) Precision water management: Mostly in areas suffering water shortages, AI-driven precision irrigation devices improve water utilization. Adapting to evolving precipitation patterns depends on these systems [115].

(4) Disaster Prediction and Response: By forecasting natural events such as floods, storms, and wildfires, AI enables timely evacuation and crop and animal protection [116].

3.10.2 Global knowledge sharing

Dealing with world agricultural problems requires information and experience on agricultural best practices, innovations, and challenges shared by everybody. Support for worldwide projects and agricultural cooperation

depends much on AI. Driven by AI, climate-smart agriculture helps to solve issues with climate change and guarantee food security. Thanks to AI, global information sharing advances cooperation, data interchange, and expertise sharing among agricultural players all around. Solving world agricultural problems and promoting a more sustainable and food-secure future depend much on these programs. Advancement of world agricultural cooperation is mostly dependent on AI. AI enables worldwide information exchange by means of the following:

(1) Data sharing platforms: Platforms driven by AI let companies, farmers, and researchers exchange data, study results, and best practices. These sites encourage cooperation and well-informed judgment [117].

(2) Language translation: AI-powered language translating technologies remove language barriers, therefore allowing agricultural specialists from all around to interact and exchange knowledge [118].

(3) Remote consultation and training: AI supports remote consultation and training programs, therefore enabling professionals to guide farmers worldwide [119].

(4) Global data integration: Global study and cooperation on agricultural challenges is facilitated by the integration and analysis of data from many sources worldwide, enabled by AI [120].

4 AI-enabled IoT architecture for smart agriculture

This section provides an introduction to the IoT architecture driven by AI intended for smart agriculture. The architecture is structured into several layers, each serving a specific purpose in the agricultural domain. These layers work together to enable data collection, processing, and decision-making to enhance farming practices and crop management.

Figure 3 illustrates a generic AI-enabled IoT architecture designed for smart agriculture. This architecture comprises five distinct layers, each with specific roles and responsibilities. These layers include the physical layer, network layer, middleware layer, processing layer, and application layer, collectively forming the framework that supports various facets of smart agricultural operations. The summary of the AI-enabled IoT architecture for smart agriculture is given in Table 2. Below, we outline the primary responsibilities of each layer.

4.1 AI-enabled physical layer

In smart agriculture, the AI-enabled physical layer pertains to the foundational infrastructure that facilitates communication and data exchange within the agricultural ecosystem.

4.1.1 Deployment layer

In the background of smart agriculture, the deployment layer involves the physical installation and configuration of IoT devices, sensors, and communication infrastructure in the field. AI plays a significant role in optimizing the deployment of these devices. It helps determine the strategic placement of sensors and actuators across the farm, ensuring comprehensive data collection and efficient communication. AI algorithms can also manage power usage and device maintenance, prolonging their operational life and reducing maintenance costs [121, 122].

4.1.2 Sensing layer

The sensing layer is where IoT sensors and devices collect data from the agricultural environment. By means of intelligent data collection and analysis, AI improves the sensing layer in smart agriculture. AI-equipped sensors can change with the times for environmental variables, including crop health, soil moisture levels, and weather patterns. To best use resources, they can independently change their measures and reporting frequency. By means of real-time insights on soil conditions, weather forecasts, and pest infestations, AI-driven analytics at the sensing layer will enable farmers to make data-driven decisions for crop management [123, 124].

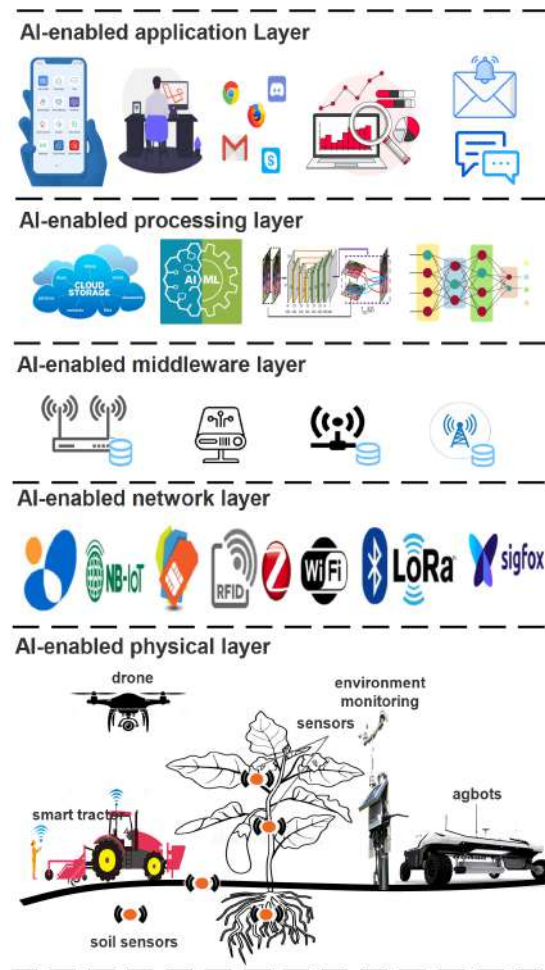


Figure 3. Generic AI-enabled IoT architecture for smart agriculture

4.2 AI-enabled network layer

In the framework of smart agriculture, the AI-enabled network layer is essential since it allows constant communication and data exchange among several devices and systems inside the agricultural ecosystem. AI fills several important tasks in this layer. Above all, it manages connectivity and communication to make sure IoT devices, sensors, and farm machinery are effectively linked using appropriate protocols, including Wi-Fi, LoRa, or cellular networks. AI in this layer optimizes network connectivity and reduces disturbance by adjusting to changing conditions [125, 126].

Moreover, network layer AI controls traffic optimization and data routing. It chooses the fastest data transfer routes, therefore lowering congestion and delay. Data from remote sensors, for example, can be routed through edge computing nodes, where AI analyzes the data, guaranteeing faster and more effective data flow [127, 128].

4.3 AI-enabled middleware layer

The AI manifested as the middleware layer is critical in smart agriculture between the data collection and processing. It has various significant purposes. First, it collects data regarding the state of soil, weather, and the health of crops by aggregating or combining the data pertaining to numerous sensors and gadgets scattered around in the agricultural environment. Second, when it comes to handling the outliers and missing values, AI technology cleans the data, standardizes the data, and transforms it into valuable form in advance before handling them

[129, 130].

Another useful application of the middleware layer is data fusion, in which AI takes information collected across multiple sources and uses it to create a comprehensive picture of the agricultural landscape. It can be in enhancing irrigation or even predicting the amount of crop produced but regardless, this vast information aids in making more accurate decisions. Moreover, this layer tends to include edge computing, a method where AI calculations are performed close to the data source, thus reducing the latency and enabling real-time field decisions, which is an essential feature of smart agriculture. Lastly, the middleware layer controls the connectivity and communication between the devices whereby the data is effectively transmitted to the processing layer to explore it further. Simply put, the AI-based middleware platform will increase the preparation of data and enable real-time and data-driven decision-making in intelligent farming [131, 132].

4.4 AI-enabled processing layer

Smart agriculture systems consist of the AI-powered processing layer, which is at the heart of the system, where data gathered through different tools and technologies are analyzed in detail to support data-based decision-making and optimize the process of cultivating crops. AI algorithm in this layer is highly efficient in analyzing data and scanning through huge numbers of data to reveal useful trends, patterns, and anomalies. These insights are then important decision support tools to the farmers, helping them know when to irrigate, add fertilizer or use pesticides, leading to resource allocation optimality and high crop yields [133, 134]. In addition, predictive models are developed by the processing layer, predicting crop harvests, risk of pest attacks, and the weather, which will give a good prospect to the farmers to organize and avert disasters. Another critical factor is automation whereby AI systems automatically operate irrigation and machinery on analyzed information in order to make operations timely and efficient. Finally, the processing layer converts other external data sources such as weather forecast and market data to provide the full picture of the agricultural landscape and make informed and strategic decisions that ultimately result in a more efficient, sustainable, and productive agricultural practice in smart agriculture [135, 136].

4.5 AI-enabled application layer

The smart farming application of AI-driven data is an epitome of the real-life application of AI-based insights. It includes irrigation automation, predictive maintenance, yield optimization, and easy to use interfaces to make decisions based on the data. Automation based on AI will guarantee the efficient use of water and the well-being of crops, whereas predictive maintenance will reduce the number of equipment malfunctions. The potential of AI in yield optimization is maximizing crop productivity to improve sustainability. DSS provides real time information to make informed decisions. Early intervention, pest and disease detection using AI and automated quality assessment of crops ensures high quality and marketability of produce. To conclude, this application layer transforms agricultural operations, lowers resource wastages, improves the harvests, and contributes to sustainability [137, 138].

4.6 Practical implementations and case studies

To prove the practical implementation of AI-based IoT architectures in smart agriculture, we will provide several examples of their implementation at various layers of our suggested framework, backed up by practical examples and published case studies.

4.6.1 Sensor Networks and Edge AI for Crop Monitoring

An excellent instance of sensor networks that are integrated with edge AI is the John Deere See 2022 State of the Art technology, See 2022, See & Spray, [139]. The system involves the use of computer vision and IoT-enabled

sprayers to detect weeds in real-time with up to 80% fewer herbicides being used to achieve crop yields. The architecture is based on edge devices (high-resolution cameras and precision sprayers) and cloud-based AI analytics to continuously improve the model. Likewise, the Watson IoT platform by IBM has been implemented successfully in vineyards in California, where webs of soil moisture sensors and microclimate stations use the information to plan schedules of irrigation using edge AI. It has been shown that this implementation has improved grape yields by 20% and has reduced water usage by an average of 15% over the conventional techniques accessible to date [140].

4.6.2 AI-Based Predictive Analytics for Yield Optimization

Microsoft's FarmBeats initiative provides an excellent case study of AI-powered predictive analytics in agriculture. By integrating data from IoT soil sensors, drone imagery, and satellite observations through Azure AI services, the system generates precise recommendations for nitrogen application and irrigation scheduling. Field trials in India have shown 10-15% improvements in water use efficiency while maintaining or increasing crop yields. Another significant implementation is The Climate Corporation's FieldView platform, which collects comprehensive field data including planting depth, soil moisture, and historical yield maps. The platform's AI models process this IoT-generated data to provide hybrid seed selection recommendations, contributing to documented yield increases of 5-10% in corn production across the country [141, 142].

4.6.3 Autonomous Robotics and AI-Driven Decision Systems

Agricultural robots that are autonomous are the most developed integration of IoT and AI. Naïo Technologies have come up with autonomous weeding robots which integrate real time computer vision with high precision mechanical instruments to weed without the use of herbicides. These robots are a component of a bigger IoT network, and they exchange field information with farm management systems. The case of Harvest CROO Robotics in Florida has dealt with the problem of labor shortages in Florida in harvesting strawberries by their autonomous pickers with its own detectors (IoT sensors) and its own path planners (AI algorithms). It takes these robots only three days to harvest a 25-acre field, which equals the performance of 30 pickers in human hands and lowers the rate of destruction of fruits by about 40% [143, 144].

4.6.4 Implementation Challenges and Lessons Learned

Regardless of the successful implementations, there are a number of challenges when it comes to executing AI-based IoT architectures on a large scale. High cost of initial IoT infrastructure is a major limitation to the small-holder farmers especially in the developing world. The problem of data interoperability often occurs as a result of the spread of proprietary data formats across various equipment manufacturers, which prevents full training of AI models. The other urgent obstacle is the energy efficiency since most edge AI devices are forced to perform at remote field areas where there is little power supply. It is promising that recent developments in low-power chip design and solar-powered edge devices can overcome this drawback. All of these case studies confirm that our proposed architecture can be practiced in the real world and that there are several areas that are worth researching and developing in the future [145].

5 Challenges and opportunities

The introduction of AI in smart agriculture is a prospective avenue of additional effective, sustainable, and robust agricultural methods. Even though this revolution is accompanied by a bundle of complex issues, not to mention a series of possibilities regarding further innovations and growth. Figure 4 shows the different challenges and opportunities in the adoption of AI in smart agriculture, and it is addressed in this article as follows.

Table 2. AI-enabled IoT architecture for smart agriculture: responsibilities, advantages, open issues, and limitations

Layer	Responsibilities	Advantages	Open Issues	Limitations
Physical layer	Hardware deployment and management of IoT devices.	-Robust sensor network -Reliable data collection -Real-time data delivery -Diverse sensor options	-Power management issues -Sensor calibration -Environmental factors -Maintenance challenges	-High initial setup costs -Limited scalability
Network layer	Ensure device connectivity and data transmission.	-Efficient data routing -Scalability -Robust communication -Load balancing	-Security concerns -Data privacy -Interoperability -Quality of Service (QoS)	-Network congestion -Latency issues -Complex setup -Compatibility issues
Middleware layer	Data aggregation and pre-processing to prepare data for analysis. Integration of external data.	-Data fusion for insights -Real-time analytics -Enhanced data quality -Edge computing support	-Data security -Integration with legacy -Data consistency -Data validation	-Complex data integration -Resource-intensive -Scalability challenges -Complex fault tolerance
Processing layer	Data analysis and insights generation for decision support.	-Predictive maintenance -Crop yield optimization	-Data privacy concerns	-Limited processing power
Application layer	Practical application of data-driven insights. Automation, prediction, and optimization of various processes.	-Enhanced farming efficiency -Real-time decision support -Resource optimization -Early pest and disease detection -Crop quality assessment	-User interface design -Integration challenges -User empowerment -Data privacy -Marketability	-Dependence on data quality -Initial setup complexity -Limited scalability

5.1 Challenges faced in implementing AI in agriculture

5.1.1 Data privacy and security

A new phase of decision-making based on data has opened with the advent of AI in agriculture. Farms are emerging as data centers, where data about the agricultural conditions, soil health, etc. is collected. As much as this flood of data is invaluable, it also raises some grave concerns about the issue of data security and privacy. Preservation of the valuable agricultural data against cyber risks and unauthorized access is very important as well as ensuring that data protection laws are adhered to. The given problems require a set of strong encryption measures, access management measures, and the education of the stakeholders on the best practices of the data security measures [146, 147].

5.1.2 Accessibility and affordability

And this comes at the cost of accessibility and affordability To reach its immense potential, AI must be accessible and affordable to every group of farmers. Smallholder farmers and farmers in the developing world may experience challenges with the adoption of AI because of the cost issue. To address the accessibility gap, bridging the divide can be achieved by creating affordable AI solutions, training and support, and creating a public-private partnership to be able to make AI technology more readily accessible to the masses of people can be achieved through the use of cost-effective AI solutions, training, and support and the creation of a partnership between the government and the commercial sector to make AI technology more accessible to the masses of people can be achieved via the creation of a partnership between the government and the commercial sector to make AI technology more accessible to the masses of people can be achieved through the creation of a partnership between the government [148].

5.1.3 Data Quality and Integration

The quality, consistency, and completeness of input data determine the effectiveness of AI in agriculture. The lack of predictability and inaccuracy of data, caused by the malfunction of sensors, missing data, and noise in the environment, may result in inaccurate predictions and poor suggestions. Because of the variety of equipment,

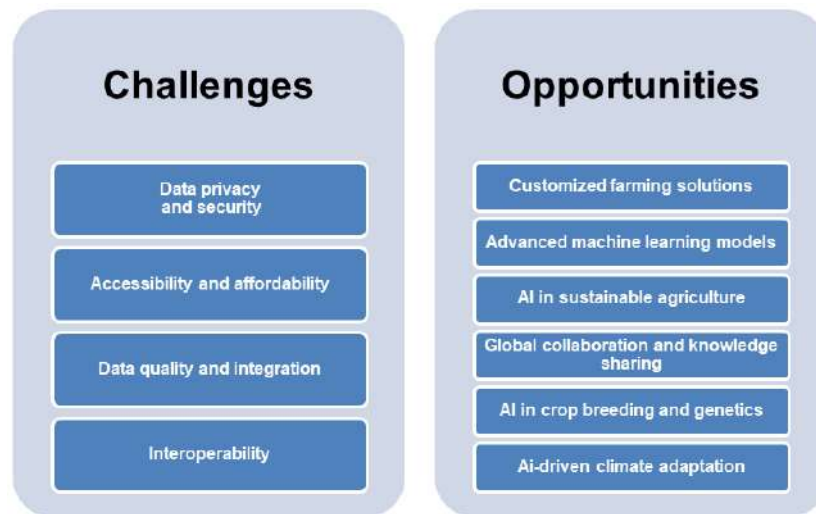


Figure 4. Various challenges and opportunities in the integration of AI into smart agriculture

vendors, and formats adopted in smart farming, the issue of integrating heterogeneous datasets is a major challenge. To solve these problems, a number of preprocessing and cleaning methods of data are used. Such ones are outlier detection (e.g., z-score filtering, boxplot), missing value imputation (mean, median, k-nearest neighbor), normalization (min-max scaling, z-score normalization), and noise removal using Kalman filtering or wavelet transforms [149]. Also, the schema alignment and semantic mapping is employed in data integration of heterogeneous data. Such techniques are necessary to ensure the presence of uniformity and compatibility of data, thus making the most out of AI in agriculture [150].

5.1.4 Interoperability

Interoperability AI applications in agriculture are provided by various vendors and in various data standards and formats. Interoperability is a problem that is found when trying to combine and apply different AI tools and systems. Open standards and the harmonization of these technologies can enhance the integration process making it easier and lowering the cost of the process and making it cost-effective [151].

5.2 Opportunities for further innovation and development

5.2.1 Customized farming solutions

Solutions tailored to individual farms AI can be used to develop custom solutions to farms. AI can provide specific recommendations based on the needs of a particular farm, its difficulties and the situation in the environment, which will help to make the process of farming more efficient, productive and sustainable[152].

5.2.2 Advanced ML models

Continued advancements in ML models, such as deep learning and reinforcement learning, would allow improving the accuracy of AI prediction in agriculture. Through real-time adaptation and learning, these models can improve their decision-making ability and management of dynamic agricultural systems which are challenging to handle [153].

5.2.3 AI in sustainable agriculture

By maximizing resource use, lowering waste, and therefore minimizing environmental effects, AI can contribute quite significant to sustainable agriculture because of maximization of resource usage, reducing wastes, and

consequently reducing the impact on the environment. Innovations in sustainable farming techniques and precision farming can lead to more environment-friendly and resilient agricultural systems that can be created in the future [154, 155].

5.2.4 Global collaboration and knowledge sharing

The global cooperation and knowledge exchange are becoming more crucial with the evolution of AI in agriculture. Through their activities and achievements, farmers, scholars, and businesses are able to share with each other, hence encouraging a universal understanding of the potential of AI in the agricultural sector and accelerating the adoption of AI everywhere in the world [156].

5.2.5 AI in crop breeding and genetics

AI would transform agricultural breeding and genetics research. ML can be used to speed up the development of stronger and more productive crop species by identifying genetic indicators of the preferred traits. This can solve the problem of food security in the world [157].

5.2.6 AI-driven climate adaptation

Agriculture will be able to adapt to the climate change modeled with the help of AI. This would enable farmers to make decisions that are more objective when it comes to their crops to ensure that they can mitigate damage in the face of altering climatic conditions, to ensure that they can utilize their resources more efficiently, and also to become more resilient to the effects of changing climatic conditions through making predictions that will be more accurate [158].

Finally, the application of AI to agriculture refers to a revolutionary chance. Though it is accompanied by multifaceted challenges, overcoming the existing challenges and capitalizing on the plethora of prospects in the field of AI usage can result in a future where AI plays a significant role in the agricultural industry by offering sustainable, efficient, and productive methods of agricultural production, global food security, and environmental protection. It is a vibrant adventure which has the possibility of updating the agricultural practices and speech and curbing certain issues that have been making waves over the years.

6 Future trends and directions

This part explores the dynamic nature of AI innovations in smart farms, the trends and technologies, and outlines where the agricultural industry may be moving with the further development of AI application.

6.1 Emerging trends in AI and smart agriculture

6.1.1 Autonomous farming

The process of self-governing farming is likely to be aggravated. Hi-tech AI-controlled machines and drones are expected to become more widespread, as they provide accuracy, productivity, and manual savings. This will transform how the farmers will be running their operations [159, 160].

6.1.2 Blockchain technology

To improve interaction in the supply chain, blockchain will have the ability to increase transparency and traceability in the agricultural industry. It guarantees that the information provided in terms of production, processing and distribution of agricultural products is true and reliable and gives the consumers an assurance of safety and quality in their food intake and consumption of food (or agricultural products) [161, 162]. .

6.1.3 AI-enhanced genomics

Genomics and breeding programs are being implemented with AI and ML to further enhance the creation of various varieties of crops that are more resistant, nutritious, and productive. This trend has captured certainty towards solving global food security issues [163, 164].

6.1.4 Quantum computing

Quantum computing can be used to revolutionize agricultural complex data analysis jobs. Initial studies indicate that it will be useful in speeding up genetic sequencing, better phenotyping of crops and bypassing major resource allocation issues more effectively than classical systems [165, 166, 180, 181].

6.2 Predictions for the future of agriculture with AI integration

6.2.1 Enhanced crop yield predictions

Further AI development will provide improved and more realistic predictions of crop yields. Farmers will also be able to have very localized and accurate forecasts and thus plan and optimize their operations in a better way to achieve this [167, 168].

6.2.2 AI-driven climate adaptation

With the climate change still threatening the agricultural sector, AI will be at the center of assisting the farmers to adjust to the shifting weather patterns. Predictive analytics will also help in crop choices and the best time to plant them, which will help to be resilient under the influence of climatic variability [169, 170].

6.2.3 AI for sustainable pest management

AI will also enhance in management of pests and disease. It will provide real time pest monitoring, early warning systems, and environmentally friendly methods of dealing with agricultural threats without the high consumption of chemical pesticides [171, 172].

6.2.4 AI-enabled soil health restoration

Soil health management will The management of soil health will be given more emphasis, and AI would help in soil analysis and suggestions on soil health restoration. Pilot experiments within the past few months have shown the application of AI-oriented models to map the soil variability and recommend specific remediation algorithms [173, 174, 182, 183].

6.2.5 Global collaboration and knowledge sharing

The agricultural community will move towards more global cooperation and exchange of knowledge. Efforts at sharing data, models and the best practices across regions can be found in digital agriculture programs and AI4Ag developed by CGIAR, among others under the first mover status of sharing knowledge in digital format [175, 176, 184, 185].

6.2.6 AI-enhanced food traceability

AI-enhanced traceability will transform the entire food supply chain, including the farm and the table. Consumers will be in a position to get information on the process of food origin and its route way, which will bring more transparency and food safety to the environment [177, 178].

AI is likely to act as one of the driving forces of the future of agriculture in the coming years. It will facilitate coordinated and sustainable and resilient agricultural activities, which can solve the global issues, such as climate change, food security, and resource protection, as well. Further in the development of AI, the agricultural industry

Table 3. Summary of the future trends and directions in the integration of AI in smart agriculture

Emerging trends			
Trend	Description	Benefits	Challenges
Autonomous Farming	Expected intensification of autonomous farming with AI-driven machinery and drones for precision, efficiency, and labor savings.	Labor savings, increased productivity.	High implementation costs, technological dependence.
Blockchain Technology	Use of blockchain for enhancing transparency and traceability in the agricultural supply chain.	Data veracity, food safety assurance.	Integration complexities, scalability.
AI-Enhanced Genomics	Application of AI and ML to genomics and breeding programs for developing resilient and nutritious crop varieties.	Accelerated breeding programs, food security.	Data quality, resource requirements.
Quantum Computing	The potential of quantum computing to revolutionize complex data analysis in agriculture.	Faster data analysis, improved models.	Limited access to quantum technology, high cost.
Predictions for the future			
Prediction	Description	Benefits	Challenges
Enhanced Crop Yield Predictions	Advanced AI models for accurate and localized crop yield predictions.	Improved planning, optimized operations.	Data accuracy, model complexity.
AI-Driven Climate Adaptation	AI's role in helping farmers adapt to changing weather patterns and crop selection.	Resilience, climate adaptation.	Data availability, model accuracy.
AI for Sustainable Pest Management	Advancements in pest and disease management with real-time tracking and eco-friendly solutions.	Reduced pesticide use, pest tracking.	Data accuracy, real-time monitoring.
AI-Enabled Soil Health Restoration	Focus on soil analysis and recommendations for soil health restoration.	Improved soil health, sustainable practices.	Soil variability, resource constraints.
Global Collaboration and Knowledge Sharing	Increasing global collaboration and data-driven best practices for food security and sustainability.	Diverse insights, collective solutions.	Data privacy, coordination challenges.
AI-Enhanced Food Traceability	Transformation of the food supply chain with AI-enhanced traceability for transparency and food safety.	Food safety assurance, consumer trust.	Data management, traceability integration.
Summary	AI's central role in shaping the future of agriculture for efficient, sustainable, and resilient practices.	Technological advancements, addressing global challenges.	Ethical considerations, data privacy, and security [179].

will keep the leading position in terms of the technological novelty, which will make agriculture not only productive but also ecologically responsible and sustainable. The Table 3 below (Tab: study-reg) captures the future trends and directions in AI integration in smart agricultural practices.

7 Conclusion

The paper has examined the disruptive role of AI in smart sustainable agriculture by indicating the use of AI in crop management, livestock monitoring, soil analysis, and environmental sustainability. One of them is the offered AI-powered IoT architecture that offers a multi-layered and structured method of utilizing data to make decisions and automate agriculture.

We have discovered the issues of data quality, privacy, system interoperability and have discussed the possible solutions, such as data cleaning methods and edge computing integration. In addition, the paper includes forthcoming interdisciplinary developments, such as AI in genomics and quantum computing, which gives the future perspective.

To the stakeholders, the work can provide them with practical information on how to adopt AI technologies to achieve efficiency, resilience, and sustainability in agriculture. It is also a guide to researchers to work on future innovations that would fit in the agenda of global food security and adapting to climate changes.

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Authors Contributions

Sarang Karim: Conceptualization, Data curation, Methodology, Writing – original draft. **Kashif Hussain:** Project administration, Methodology, Writing-original draft. **Muhammad Bux Alvi:** Data curation, Formal analysis, Writing – original draft. **Mushtaque Ahmed Rahu:** Formal analysis, Writing—review and editing. **Mumtaz Ali Kaloi:** Data curation, Writing—review and editing. **Halar Haleem:** Data curation, Writing—review and editing.

Compliance with Ethical Standards

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper. Ethical approval is not applicable. All authors consented to participate and to publish this work. All supporting data for this study are available from the corresponding author upon reasonable request.

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