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Review

Artificial Intelligence Tools for the Agriculture Value Chain: Status and Prospects

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Abstract: This article explores the transformative potential of artificial intelligence (AI) tools across the agricultural value chain, highlighting their applications, benefits, challenges, and future prospects. With global food demand projected to increase by 70% by 2050, AI technologies—including machine learning, big data analytics, and the Internet of things (IoT)—offer critical solutions for enhancing agricultural productivity, sustainability, and resource efficiency. The study provides a comprehensive review of AI applications at multiple stages of the agricultural value chain, including land use planning, crop selection, resource management, disease detection, yield prediction, and market integration. It also discusses the significant challenges to AI adoption, such as data accessibility, technological infrastructure, and the need for specialized skills. By examining case studies and empirical evidence, the article demonstrates how AI-driven solutions can optimize decision-making and operational efficiency in agriculture. The findings underscore AI's pivotal role in addressing global agricultural challenges, with implications for farmers, agribusinesses, policymakers, and researchers. This article aims to advance the evolving research and discussions on sustainable agriculture, contributing insights that promote the adoption of AI technologies and influence the future of farming.

Keywords: precision agriculture; artificial intelligence; value chain; sustainability

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1. Introduction

The agricultural value chain includes activities ranging from farm production to product logistics and sales of agricultural products to consumers, has traditionally involved processes that are executed manually and are labor-intensive. Nevertheless, in the past few decades, advancements in the field of technology have been undertaken throughout this value chain, leading to improvements in productivity and efficiency, as well as enhanced sustainability. Sustainability, in particular, emerges as a key goal, especially considering the increasing population and the associated increase in the need for food supply and food security. Technological innovations can play a key role in achieving these goals; among these innovations, artificial intelligence (AI) has already been leveraged to transform numerous processes within the agricultural value chain, ranging from crop selection and disease detection, to resource use and logistics optimization [1,2]. AI, combined with other technologies, such as the Internet of things (IoT) and robotics, may be exploited in task automation, analysis of large data volumes, and the formulation of data-driven and explainable recommendations, leading to the improvement of agricultural practices. In turn, advancements in agricultural practices can underpin the goal of meeting the growing global demand for food and food safety [3,4], and assisting in tackling important challenges, notably including climate change [5,6].

Climate change and environmental sustainability are closely related to the optimization of resource use, including water, pesticides, and fertilizers. Towards this goal, data sourced from sensors provide real-time information regarding the condition of the field, the crops and surrounding factors (e.g., weather forecasts), and AI-based systems offer recommendations on the actions that need to be taken; these actions can be executed automatically (e.g., by automated irrigation systems) or manually [7,8].

The agricultural value chain comprises multiple steps, including the planning of field use, sawing, cultivation, disease prevention, detection and treating, processing, storage, transportation, and distribution of agricultural products. Each of these steps is inherently complex and requires a substantial amount of expertise, while the diversity and interdependence of these steps introduce additional barriers to the overall optimization of the agricultural processes. AI systems provide a means to formulate optimal agricultural process plans, streamlining the related processes, reducing waste, and improving value chain efficiency both at the global level [9,10] and at the individual stage level [11–13].

This paper explores how AI can be effectively utilized in the context of the agricultural value chain to improve productivity, sustainability, and profitability. The paper considers the use of AI in agricultural processes including planning, resource management, cultivation, disease identification, and yield prediction, aiming to systematically record and analyze the contribution of AI to the agricultural value chain [14,15]. The results of this study can be exploited by stakeholders such as farmers, agricultural cooperatives, agribusinesses, and policy makers to gain insight into the use and the benefits of AI-based technologies in the agricultural sector [16,17], supporting the improvement of agricultural processes [18,19] and the achievement of global goals, including food safety [3,4] and resilience to climate change [5,6]. Additionally, insights on the future use of AI applications in agriculture [9,20] are offered. These findings can be combined with insights and experiences gained from real-world applications of AI-based methods in the agricultural value chain, such as: (a) the Farmspace organization, which has deployed low-cost portable AI-powered soil testing devices across more than 3000 farms, allowing farmers check their soil's health status and analyze its fertility on the field in real time [21]; (b) Demeter, an AI-based speed-rowing machine, which performs mechanized harvesting on fields, optimizing paths and avoiding obstacles [22]; the NetSens live data platform, which collects information from agrometeorological stations and uses AI-based models and methods to predict disease outbreaks and provide advice on the use of plant protection [23] with a focus on vines [24]; and (d) the Nindamani the Weed Removal Robot, which autonomously detects and segment the weeds from crop using artificial intelligence [25].

This article focuses on the following research objectives:

- RO1. To explore how can AI-based tools improve land use planning and crop selection to enhance agricultural productivity and sustainability.
- RO2. To identify which are the most effective AI-driven strategies for optimizing resource management, including water use, fertilizer application, and energy efficiency.
- RO3. To determine and document how AI contributes to precision agriculture, particularly in optimizing planting schedules, irrigation, and crop monitoring.
- RO4. To highlight the potential benefits of AI in early disease detection and yield prediction and establish whether these applications can contribute to the mitigation of risks in agriculture.
- RO5. To survey how AI can be integrated into agricultural logistics to reduce waste, improve efficiency, and enhance market access for farmers.
- RO6. To identify the future prospects for AI in transforming the agricultural value chain, and the challenges that must be addressed to realize its full potential.

By pursuing these objectives, the article will provide a comprehensive overview of the status and prospects of AI tools in agriculture, offering insights that are crucial for advancing the sector in a sustainable and efficient manner. The paper contributes to the literature on the role of AI in agriculture (e.g., refs. [26–28]) in the following respects:

1. It comprehensively covers the agricultural cycle, from land usage planning and crop selection to price prediction and logistics. This feature is unique among existing surveys; for instance, ref. [26] does not cover land planning and crop selection, while resource management is limited to irrigation and soil control, omitting areas such as energy consumption.
2. It elaborates on the AI algorithms used for each stage of the agricultural production cycle, while some other surveys explore only the application level (e.g., ref. [26]) or provide only generic aspects of the AI-based process, e.g., image segmentation and desired output [27];
3. It takes into account newly published research (mainly in the years 2023 and 2024).
4. We discuss challenges and limitations of AI-based approaches, including technical challenges, economic and social barriers, and ethical considerations. This information will allow stakeholders to prepare holistic implementation plans, which take into account potential issues and include relevant mitigation plans.

The rest of the paper is structured as follows. Section 2 presents the data collection method and process. Section 3 discusses how AI enhances land use planning and crop selection in agriculture, enabling precise analysis of soil, weather, and topography. It highlights AI's role in optimizing agricultural practices and improving crop yields through data-driven decisions. Section 4 focuses on AI's impact on precision agriculture, detailing its integration with drones, sensors, and robotics. AI optimizes planting, irrigation, and crop monitoring, while also advancing autonomous farming technologies like AI-driven planting and harvesting. Section 5 explores AI's application in identifying and managing plant diseases. It focuses on AI-powered image recognition and predictive modeling for early disease detection, by presenting case studies which demonstrate the effectiveness of AI in improving crop health. Section 6 outlines the role of AI in predicting crop yields using weather and soil conditions, as well as historical data. Furthermore, it presents how AI integrates yield predictions with market trends, aiding decision-making for farmers and improving agricultural efficiency. Section 7 explores the importance of AI in forecasting agricultural prices, using deep learning and machine learning models. More specifically, it demonstrates how environmental, economic, and market data are combined in order to accurately predict prices, as well as it presents the challenges and future prospects for this research area. Section 8 outlines how AI manages to optimize agricultural logistics such as transportation, storage, and distribution by including examples of waste reduction, efficiency improvement, and market access facilitation for farmers through price prediction and demand forecasting. Section 9 discusses the issues of the adoption of AI in agriculture, including ethical concerns, such as data privacy and job displacement, economic barriers, and various technical issues, by emphasizing the need for responsible AI integration. Section 10 looks at emerging AI trends in agriculture, such as deep learning, blockchain, and IoT. It discusses AI's potential to enhance global food security and sustainability, and the role of policies in supporting AI adoption while addressing key challenges. Section 11 presents examples of use cases for AI algorithms. In Section 12, we discuss the findings of our survey and present the answers to the research objectives formulated above. Finally, in Section 13 conclusions are drawn, research findings are summarized, and future research directions are listed.

2. Data and Methods

The purpose of this paper is to survey the current situation and prospects for the use of AI Tools in the agricultural value chain. The methodology used for identifying relevant work follows the PRISMA approach (Figure 1), a rigorous and organized approach for examining and synthesizing bibliographic resources published in the literature. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) approach is a widely used framework to improve the transparency and quality of reporting in systematic reviews and meta-analyses. It was developed to ensure that systematic reviews follow a consistent, rigorous, and transparent methodology, and to minimize biases in the research process [29].

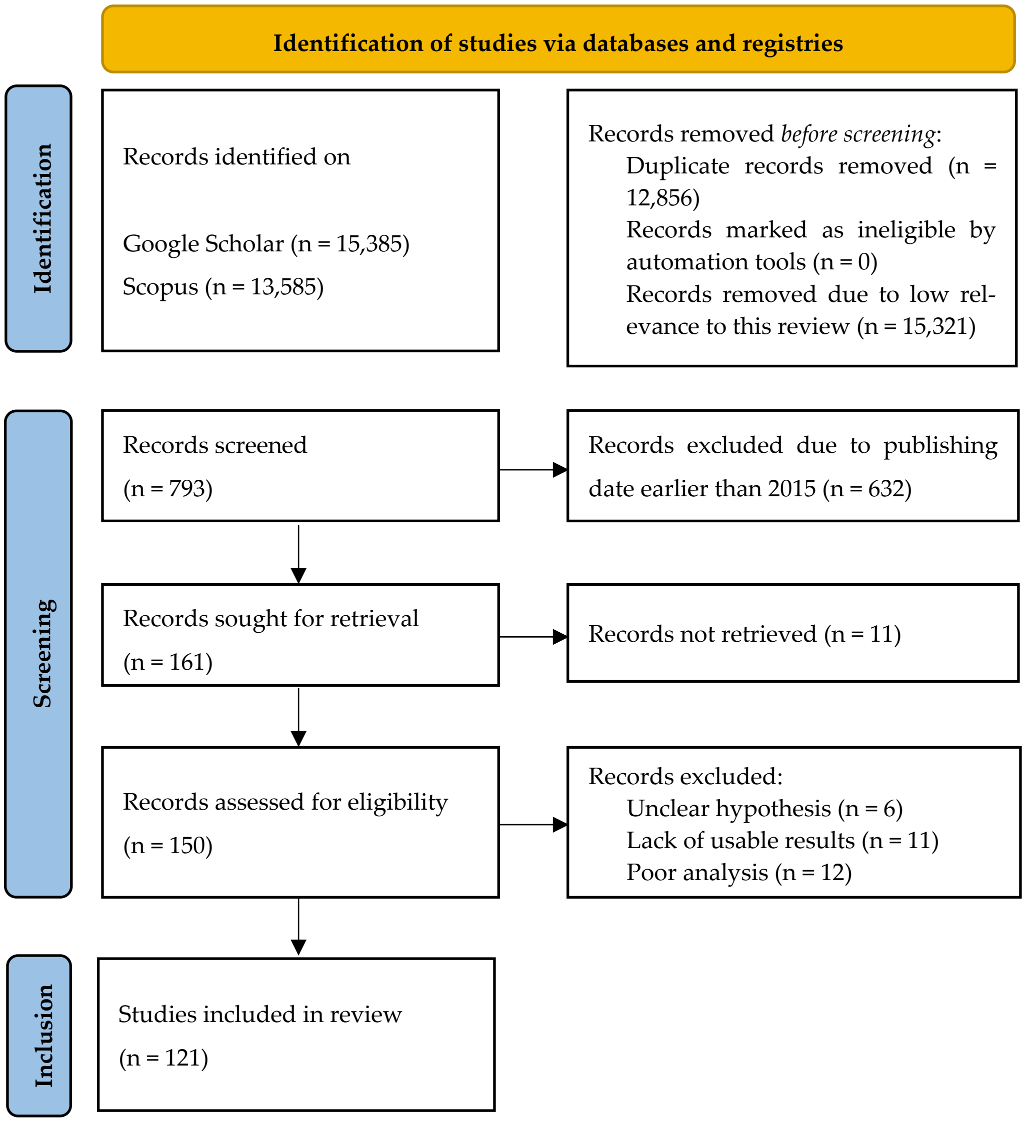

Figure 1. PRISMA flowchart for the set of keywords on the use of AI Tools for the Agriculture Value Chain.

In order to collect the bibliographic resources, publications focusing on the topic of the paper, and the above listed research objectives in particular, were located and examined. Selected important works served a double role: Firstly, they contributed to the material pertaining to the research objectives addressed by this paper. Secondly, their reference list used a list of additional resources to be examined. Scientific publication databases constituted a key source for the identification of relevant publications. Both the Scopus platform and Google Scholar were used in the context of this work. These platforms provide higher coverage of scientific literature than the Web of Science platform [30–32]. While Google Scholar provides metadata of lower quality compared to Scopus, we decided to include them in the data collection process since its database is a superset of that of Scopus [33,34]. A considerable number of works were identified in both sources, and in these cases the results from Scopus were utilized, due to their higher metadata quality.

Table 1 lists the basic sources used for data retrieval and for the identification of additional sources.

Table 1. Basic sources for data retrieval and for identification of additional sources.

Source Type	Description	Year of Publication	Use
Scientific publication	Applying big data for intelligent agriculture-based crop selection analysis [35]	2019	Extracting data and identifying new scientific publications.
Scientific publication	A comprehensive review of agriculture irrigation using artificial intelligence for crop production [27]	2022	Extracting data and identifying new scientific publications.
Scientific publication	Application of artificial intelligence (AI) and IoT in Agriculture: A Systematic Literature Review [26]	2022	Extracting data and identifying new scientific publications
Scientific publication	Towards automatic field plant disease recognition [28]	2022	Extracting data and identifying new scientific publications.
Scientific publication	Machine Learning- and Feature Selection-Enabled Framework for Accurate Crop Yield Prediction [15]	2019	Extracting data and identifying new scientific publications.
Scientific publication	Time Series Forecasting of Price of Agricultural Products Using Hybrid Methods [36]	2021	Extracting data and identifying new scientific publications
Scientific publication	Convergence of Distributed Ledger Technologies with Digital Twins, IoT, and AI for fresh food logistics: Challenges and opportunities [37]	2023	Extracting data and identifying new scientific publications
Database	Scopus		Extracting data using queries.
Database	Google Scholar		Extracting data using queries.
Internet			Searching for programs and directions.

Pertinent scientific papers were identified through the Scopus [38] academic database by utilizing suitable search criteria (Table 2). To retrieve the results relevant to the goals of this study, we formulated search queries as illustrated in the following table. Please note that in the second query, the placeholder text *keywords for the specific research objective* were appropriately substituted by suitable keywords that define the research objective at hand, e.g., "disease recognition", "logistics", or "price prediction". In all cases, the papers were limited to those published in the last 10 years, so that they include the latest developments in the relevant fields. Notably, most works retrieved have been published since 2019, probably owing to the latest AI developments that enabled its more widespread use, including the introduction of transformers [39].

Table 2. Search queries used to locate scientific publications in Scopus.

Description	Query
Query for the articles on the topic of the paper.	TITLE-ABS-KEY ((ai OR (artificial AND intelligence) OR (machine AND learning) OR (deep AND learning)) AND (agriculture OR agricultural) AND (value AND chain)) AND PUBYEAR > 2015
Query for the articles related to a specific research objective.	TITLE-ABS-KEY ((ai OR (artificial AND intelligence) OR (machine AND learning) OR (deep AND learning))) AND TITLE-ABS-KEY (*keywords for the specific research objective*)) AND PUBYEAR > 2015

A similar approach was used for retrieving results from the Google Scholar database; however, due to the fact that Google Scholar does not allow the specification of the constraint that the search query elements must appear in the title, abstract or keywords, results from Google Scholar were processed as follows:

- Firstly, it was verified whether the result had already been retrieved by a Scopus query; if it had indeed been retrieved, the result was retained;
- Otherwise, the title, abstract, and keywords were read by the research team, to verify that the search keywords were indeed present in these publication elements.

3. AI in Planning

3.1. Land Use Planning

3.1.1. AI-Based Tools for Analyzing Soil Quality, Weather Patterns, and Topography

AI-based tools are becoming indispensable in modern agriculture, particularly in land use planning, where they offer advanced capabilities for analyzing critical factors such as soil quality, weather patterns, and topography. These tools employ sophisticated machine learning algorithms, big data analytics, and IoT-enabled sensors to process extensive datasets from various sources, including remote sensing, soil samples, and historical weather records. For instance, AI models like support vector machines (SVM) and decision trees are utilized to predict soil health by analyzing key parameters such as pH levels, organic matter content, and the availability of essential nutrients like nitrogen, phosphorus, and potassium [7,40]. Relevant data are sourced by traditional manual analysis procedures (soil collection and processing in the lab), or by employing modern, IoT-based methods, e.g., hyperspectral sensors [41].

Moreover, AI tools allow farmers to simulate different scenarios related to climate change, including droughts, floods, water shortage, and heatwaves, and prepare accordingly, improving resilience and minimizing potential losses [2]. These tools incorporate information from topographical data and hence can aid in the selection of suitable terrain for specific crops, based on factors like slope, drainage, or microclimate variation. As a result, by integrating data concerning high-resolution satellite images into AI-based models, farmers are able to make decisions about the maximum potential of land yielding allocation [18]. For example, NDVI (normalized difference vegetation index) measurements from satellite image processing of soil and weather conditions have been proven to be very effective for crop health estimation and yield prediction based on [1].

This methodology enables the reader to understand how environmental covariates interact to improve spatial strategies in planting for yield performance more comprehensively [13].

3.1.2. Optimal Crop Selection and Agricultural Practices

The use of AI applications allows farmers to choose the perfect crop and agricultural practice for optimal results in agriculture, making it possible to obtain higher yields with more sustainable practices. AI-based systems, such as the Crop Selection Method (CSM), employ machine learning algorithms like gradient boosted decision trees (GBDT) and random forests to draw insights from past performance of crops, such as yield measures. By incorporating physical environmental data, agronomic traits (e.g., disease resistance characteristics), and phenological attributes (e.g., duration of growth cycles), they are able to recommend the varieties that are more likely to succeed under given soil and climate dimensions, as well as optimal planting and harvesting schedules [7,40]. The work in [40] also reports on the application of artificial neural networks (ANN) to the same goal, with superior results as compared to SVM models. In particular, multiple ANN models were tested, with general regression neural networks (GRNN) achieving the best results, with a prediction accuracy equal to 92.86%, while SVM result accuracy was equal to 83%.

Similarly, the work in Shams et al. [18] develops an intelligence-based crop recommendation system, namely XAI-CROP, which promotes transparency in the agriculture assistive decision-making process. This system provides farmers with personalized crop recommendations using soil type information, regional weather patterns, and historical crop yield data. By including explainable AI (XAI) techniques, XAI-CROP is able to provide recommendations that are not only accurate but also interpretable by farmers, thus increasing not only the recommendation but also the adoption of the technology.

The use of AI tools in India has already proven to be a game-changer for the selection of rice and wheat varieties. These methods are used to produce higher yields, improve resistance to pests and invasive species of bacteria, and promote better acclimation with the surrounding environment [42]. Such AI applications have been extended to crop rotation planning, providing management strategies derived from models such as Deep Q-Networks (DQNs) for creating sequences of crops. These sequences are based on either economic returns or soil health, and hence perform better in nitrogen demand, sustainability guidelines, etc. [1].

The success of AI applications is not limited to crop selection, but it is also extended to agricultural practices in general. For example, combined decision-making tools that use dominance-based raw set approaches (DRSA) and machine learning models have been developed to support farms in selecting the most appropriate crops based on multiple criteria, including soil characteristics, water availability, seasonal factors, etc.

In their study, Deepa and Ganesan [13] showed the effectiveness of such a tool, developed using DRSA dominance, in calculating the weights of various sub-variables, as well as that of Johnson's reduction algorithm when applied to generating classification rules for crops such as paddy, sorghum, and sugar cane. The tool accurately predicted the best crop in over 92% of cases, closely aligning with expert recommendations [13].

AI-based systems have also been particularly successful in enhancing crop diversity and resilience, as they have the ability to process critical factors such as disease resistance, adaptability to changing climate conditions, and market trends [8]. By incorporating sensor networks and neural networks, such as multi-layer perceptrons (MLP), they assess the suitability of land for different crops, classifying it into categories such as most suitable, suitable, moderately suitable, and unsuitable. This classification enables farmers to make data-driven decisions, driving their crops to higher yields and implementing more efficient use of resources [43].

Also, the use of big data combined with IoT in intelligent agricultural systems has proven effective in the accurate selection of crops that can be grown in specific environmental conditions. According to his study, Tseng [35] showed how three-dimensional cluster analysis can be used to group environmental factors and determine suitable crops for specific farm conditions. This system not only monitors and analyzes soil and climate conditions, but also provides useful information to farmers about what kind of crops are most likely to prosper, thus improving agricultural results.

In Table 3 we summarize the AI algorithms used for land use planning and crop selection. For each algorithm, the relevant use cases are listed, and the strengths and limitations for each algorithm are given.

Table 3. AI algorithms used in land use planning and crop selection.

AI Algorithm	Use Case	Strengths	Limitations
Machine Learning (General)	Predicts optimal land use and crop selection	Adaptable, scalable to multiple scenarios	Requires careful data curation
Gradient Boosted Decision Trees (GBDT) [7,40]	Predicts land use efficiency and crop suitability	High accuracy, reduces overfitting	Slower to train on large datasets
SVM [7,40]	Classifying land for optimal use and crop suitability based on factors like soil type, climate, and terrain	High accuracy, works well for small datasets, effective in high-dimensional spaces	Computationally expensive for large datasets, difficult to interpret

Table 3. *Cont.*

AI Algorithm	Use Case	Strengths	Limitations
Random Forests [7,40]	Predicting optimal land use and crop selection based on soil, weather, and historical data	Handles high-dimensional data well, robust to overfitting, interpretable	Requires large training datasets, computationally intensive for large models
Deep Q-Networks (DQNs) [1]	Reinforcement learning for land management	Learns from real-time feedback, adaptive	Requires continuous retraining
Dominance-based Rough Set Approach (DRSA) [13]	Decision-making for land allocation and crop selection	Handles uncertainty in decision-making	Sensitive to data quality
Multi-Layer Perceptron (MLP) [43]	Neural network model for crop prediction	Good for non-linear problem-solving	Prone to overfitting, hard to interpret
XAI-CROP [18]	Explains AI decisions for crop selection	Transparent, explainable outcomes	Requires complex, explainable models
Artificial Neural Networks (ANN) [40]	Predicting optimal land use and crop selection based on soil, weather, and historical data	High accuracy, can be used with small datasets.	Multiple ANN models and hyper-parameters need to be tested.

3.2. Resource Management

3.2.1. Efficient Water Use, Fertilizer Application, and Energy Management

AI technologies are increasingly being used in optimizing resource management in agriculture, particularly in the areas of water use, fertilizer application, and energy management. AI-powered irrigation systems use real-time data from soil moisture sensors, weather forecasts, and crop water needs to manage water resources more efficiently. This ensures that crops receive the right amount of water at the right time, significantly reducing wastage and improving crop health [8]. Also, corresponding models analyze the soil nutrient profile and crop growth stages to determine the correct amount and ideal time of fertilizer application. This approach maximizes crop yields but also minimizes the environmental impacts associated with over-fertilization, such as nutrient runoff, soil degradation, and water table stress [1].

In greenhouse applications, AI-based energy management systems are being developed to improve the use of heating, lighting, and ventilation and adjust these parameters in response to real-time data. This results in significant reductions in energy consumption and operating costs, while maintaining ideal growing conditions for the plants. For example, AI systems developed in Dutch greenhouses have been shown to reduce energy consumption by up to 15%, demonstrating the potential of AI to contribute to more sustainable agricultural practices [13].

3.2.2. Case Studies or Examples of AI-Based Resource Management Systems

Numerous case studies have been developed that highlight the effectiveness of AI-based resource management systems in agriculture. In Australia, they have successfully implemented water management systems that, using AI, have led to significant water savings and improved crop productivity. These systems use machine learning algorithms to predict water needs and optimize irrigation schedules taking into account real-time soil moisture data and weather forecasts [2].

Another example is the systems in Dutch greenhouses that are used to optimize energy consumption by adjusting heating and lighting based on data from plant growth stages and external environmental conditions in real time. This approach reduced the consumption of electricity but also maintained the optimal growing conditions, thus highlighting the effectiveness of AI in the management of energy resources in agriculture [13,18].

AI-based systems are used in organic agriculture, and they develop reinforcement learning models by creating crop rotation sequences to optimize soil nitrogen levels, thereby improving long-term soil fertility and crop yields. These systems use real-time data to ensure that rotations are aligned with economic and environmental sustainability goals, making them essential tools for modern agriculture [1].

Also, a successful example is sensor-based AI models that have demonstrated significant improvements in land suitability assessments in Tamil Nadu, India, leading to more efficient water use and better crop yields. These AI systems integrate data from various sensors in real time to optimize irrigation schedules while maintaining high levels of productivity. Additionally, these systems have been proven to achieve high accuracy in land classification, helping farmers optimize their resource use and crop productivity [43].

Another important case study is the platform developed by Tseng, which combined IoT sensors with big data analytics to optimize crop selection and farm resource management using appropriate AI models. This platform helped increase water use efficiency and improved crop yields by providing real-time information and recommendations based on continuous environmental monitoring [35].

All the aforementioned examples indicate the potential of AI to make agricultural practices more sustainable and resource-efficient, thus contributing to the overall resilience of the agricultural value chain.

In Table 4 we summarize the AI algorithms surveyed in this section in the context of resource management. For each algorithm, the relevant use cases are listed, and the strengths and limitations for each algorithm are given.

Table 4. AI algorithms used in optimization of resource management (water, fertilizers, energy).

AI Algorithm	Use Case	Strengths	Limitations
Particle Swarm Optimization (PSO) [44,45]	Water and Fertilizers optimization for efficient irrigation	Fast convergence, flexible	Sensitive to initial conditions
Random Forest [46]	Predicts water/fertilizer requirements based on sensor data	High accuracy in predictions	Requires a large amount of training data, may incur high computation costs
Gradient Boosting Machines (GBM) [47]	Fertilizer application optimization based on crop type and soil health	Accurate, robust to outliers	Slow training times for large datasets
Deep Learning (CNNs, RNNs) [48]	Energy and water usage prediction	Handles complex temporal patterns (weather)	Requires significant computational resources

4. AI in Cultivation

4.1. Precision Agriculture

4.1.1. The Role of AI in Precision Farming

AI plays a significant role in the evolution of precision farming, while its advanced technologies, such as drones, sensors and robotics, significantly enhance the efficiency and accuracy of agricultural practices. As far as drones are concerned, they include AI-driven imaging systems, as well as hyperspectral, multispectral, and thermal cameras, which enable them to capture real-time and detailed data concerning crop health, soil conditions, and environmental variables across large agricultural fields (e.g., ref. [41]). The high-resolution images taken are then processed by machine learning algorithms in order to identify patterns and anomalies, a task which it would be difficult to effectively accomplish using traditional methods [5,27]. For example, drones are able to monitor crop growth, detect stress (e.g., due to pests or diseases), and evaluate moisture levels, thus providing critical information that informs decision-making throughout the growing season.

Imagery data can be complemented by field condition data sourced from sensors deployed throughout fields, which continuously measure environmental factors such as soil moisture, pH levels, temperature, and nutrient availability. Diverse data sources are fused in a unique data stream, which is fed into AI models that can predict crop needs in real time, enabling precise adjustments to irrigation, fertilization, and other inputs. Such systems help in optimizing resource use, reducing waste, and minimizing the environmental impact of farming practices [14].

Robotics, another key component of AI in precision farming, are designed to perform repetitive tasks such as planting, weeding, and harvesting with unparalleled precision. These robots are equipped with AI algorithms that enable them to navigate complex field environments autonomously, making real-time decisions based on sensory data [14].

4.1.2. Benefits of AI in Optimizing Planting Schedules, Irrigation, and Crop Monitoring

The integration of AI into precision agriculture brings substantial benefits, particularly in optimizing planting schedules, irrigation management, and crop monitoring. AI models utilize vast datasets, including historical climate data and real-time weather forecasts, to predict the optimal times for planting. By ensuring that crops are sown under the most favorable conditions, farmers can significantly improve yield potential while mitigating risks associated with weather variability [4].

In the area of crop monitoring capability enhancement, the studies in [49,50] report on AI-based systems that process data from drones, sensors, and other monitoring technologies using advanced machine learning algorithms to detect early signs of stress in crops, such as disease onset, pest infestation, or nutrient deficiency. For instance, AI-powered systems may analyze input data streams and use indications such as leaf color changes, shape anomalies, or temperature modifications to identify potential disease outbreaks in a timely fashion, even before these symptoms could be traceable through visual inspection. Early diagnosis is extremely important, since it gives farmers the ability to measure fertilizers and pesticides to selected farming areas, create effective strategies to preserve plant health and avoid yield loss, etc.

Besides increasing operational efficiency, AI-enabled precision agriculture practices also increase the sustainability of farming, by minimizing input utilization such as water, fertilizers, and pesticides (and hence reduce environmental impacts across agricultural activities) (c.f. Section 3). As AI technology further matures, its integration in precision farming will grow and provide even more advanced means to handle intricate agricultural systems [4].

In Table 5 we summarize the AI algorithms surveyed in this section, concerning the optimization of planting scheduling, irrigation, and crop monitoring. For each algorithm, the relevant use cases are listed, and the strengths and limitations for each algorithm are given.

Table 5. AI algorithms used in optimizing planting schedules, irrigation, and crop monitoring.

AI Algorithm	Use Case	Strengths	Limitations
SVM [51,52]	Classifying crop health conditions	High accuracy for binary classification problems	Computationally expensive on large-scale data
Long Short-Term Memory (LSTM) [53,54]	Forecasting crop growth, irrigation needs based on weather	Effective for long-term dependencies	High computational cost
Recurrent Neural Networks (RNNs) [55]	Predicting optimal planting times based on weather and soil data	Handles sequential data, good for time-series forecasting	Difficult to train, slow to converge
Convolutional Neural Networks (CNNs) [56]	Image-based monitoring of crops using drones/satellites	Excellent for pattern recognition from images	Requires large amounts of labeled data

4.2. Automation and Robotics

4.2.1. Use of AI in Autonomous Farming Machinery

The inclusion of AI in autonomous farming machinery is a major leap forward concerning agricultural automation.

Based on the observations they make, these AI-driven machines, equipped with sensors, cameras, and GPS technology which enable them to navigate fields accurately and act on the fly, are able to (semi-)autonomously undertake various agricultural tasks, such as land preparation and planting, weeding, harvesting, etc. [14]. They are also equipped with AI algorithms, enabling them to differentiate crops from weeds, check soil quality, and alter their operations accordingly. Autonomous operation reduces the dependence of human labor, which is crucial in areas of labor shortage, while it also leads to more consistent and accurate task execution that delivers high productivity and lower operating costs [5].

4.2.2. Automated Planting, Weeding, and Harvesting

The high-sensitivity sensors and analysis tool of AI in implementing robotic planting systems can also benefit them by examining soil properties, such as moisture content, texture, and compaction, during real-time operation. Based on this information, AI algorithms are able to compute the optimal planting depth and spacing for seeds to facilitate the process from germination to the early growth stage. This accuracy in seeding results in an even crop emergence and thus maximizes yield potential [14].

As far as the weeding process is concerned, AI has enabled technology to develop autonomous weeding robots with machine vision and deep learning algorithms that are able to accurately distinguish between crops and weeds with a high level of precision. These robots can accurately detect and remove weeds, even in high-density crop fields, without damaging the crops. Implementing weed management—rather than brush application of chemical herbicides—on all crops promotes more sustainable agricultural practices and reduces the environmental impact of farming activities [5]. Furthermore, these weeding robots are able to work around the clock, serving large indoor or outdoor farming areas with a higher efficiency of weed control compared to that of human labor and traditional chemical use.

AI is turning harvesting (which is one of the most labor-intensive jobs in agriculture) into a task for machines. Extractor robots are AI-controlled robots equipped with sensors and cameras, which enable them to investigate the maturity of natural products by analyzing characteristics such as shape, size, and color. By using advanced AI algorithms, these robots are able to determine the optimal time for harvesting, ensuring that only the ripe products are selected. This approach manages to minimize waste, while at the same time enhancing the quality and market value of the harvested crops [50,57]. Additionally, the use of AI in harvesting also minimizes the reliance on seasonal labor (which is both hard to rely on and costly) and provides consistent 24/7 operational capabilities leading to increased productivity

The examples of AI in automated planting, weeding, and harvesting underscore the transformative effect of AI on modern agriculture. By automating these crucial tasks, AI not only enhances operational efficiency but also promotes sustainability and profitability in agricultural practices. As AI technology continues to evolve, its role in agriculture is anticipated to grow, providing increasingly sophisticated tools to manage complex agricultural systems with greater precision and reduced environmental impact [14].

In Table 6 we summarize the AI algorithms surveyed in this section, concerning the optimization of planting scheduling, irrigation, and crop monitoring. For each algorithm, the relevant use cases are listed, and the strengths and limitations for each algorithm are given.

Table 6. AI algorithms used in automated planting, weeding, and harvesting.

AI Algorithm	Use Case	Strengths	Limitations
Convolutional neural network [5]	Target detection algorithm	High accuracy	Large memory footprint, needs considerable amount of labeled data

Table 6. *Cont.*

AI Algorithm	Use Case	Strengths	Limitations
Faster R-CNN [50]	Weed identification in maize, sugar beet, and wheat crops	Operational efficiency, accuracy	Degraded performance with background clutter or noise in images; need for large datasets
CNN [50]	Weed classification in 22 different crops	Classification accuracy	Need for large datasets, high computational requirements
RNN [57].	Weed identification and classification	Classification accuracy	Vanishing and exploding gradients in the learning process

5. AI in Disease Recognition

5.1. Disease Identification

5.1.1. AI-Powered Image Recognition Systems for Detecting Plant Diseases

AI-powered image recognition systems have become instrumental in identifying and diagnosing plant diseases with high accuracy, particularly through the use of convolutional neural networks (CNNs). These deep learning models automatically extract features from images of plant leaves and classify them according to the type of disease. For example, Mohanty trained a deep learning model to recognize 14 crop species and 26 crop diseases, achieving an accuracy of 99.35% on the test set [12,58]. Similarly, Brahimi successfully applied CNNs to classify tomato diseases with 99.18% accuracy [59], while Guo [60] developed a multiscale AlexNet model on an Android platform for disease identification from tomato leaves [20].

Recent advancements in these systems include the integration of techniques such as background replacement and leaf resizing, which have significantly enhanced the robustness of CNN models under real field conditions. For instance, the application of these methods to the Field-PlantVillage dataset led to an accuracy improvement from 41.81% to 72.03% [28]. Vision Transformers (ViT) have also been considered in AI systems as a successful processing approach for images with complex backgrounds, such as the ones included in the PlantDoc dataset. The PMF+FA technique, which combines few-shot learning (FSL) with a feature attention module, was able to score over 90% accuracy on challenging datasets, demonstrating its effectiveness in real-world scenarios [11].

Furthermore, the evolution of advanced models, such as the YOLOv5, has given even more power to the AI-based image recognition systems. This model includes improvements such as the InvolutionBottleneck and the SE modules. The first one is able to reduce the computational overhead while gathering long-range spatial dependencies, while the second one is able to improve the sensitivity of the model to different feature channels. The inclusion of these modules to the YOLOv5 model resulted in significant accuracy increases, achieving 86.5% accuracy for powdery mildew detection and 86.8% for anthracnose in rubber trees [61,62].

The real-time monitoring and detection of crop diseases, using UAVs combined with ground-based sensors, has been revolutionized by AI integrated robotic systems, as shown above in the case of Agriculture 5.0. This supplementary method not only augments the precision and endemics of interventions, but also identifies early symptoms that are imperceptible to humans and thus helps to prevent large-scale crop losses [63].

5.1.2. Early Disease Diagnosis and Intervention

AI applications in early disease diagnosis play a crucial role in mitigating the spread of disease and enhancing crop yields. These systems enable timely interventions, reducing the need for chemical pesticides and preventing substantial crop losses. For instance, Kawasaki developed a CNN-based system specifically designed to detect early disease symptoms in cucumbers, achieving an accuracy of 94.9% [64]. Similarly, Xie demonstrated the use of hyperspectral imaging combined with deep learning models for the early detection of tomato leaf diseases, achieving a classification accuracy of 97.1% [65].

Advanced techniques, such as few-shot learning (FSL) methods, have also proven effective in early disease diagnosis, even when limited training data is available. For example, the PMF+FA method achieved high accuracy in recognizing plant diseases, with only five images per class, proving to be a very useful tool in dynamic agricultural environments, where data may be scarce [28]. Furthermore, data augmentation techniques in CNN models, including background replacement and leaf resizing, have improved early disease detection in field conditions, enhancing accuracy while at the same time speeding up intervention strategies [28].

The improved YOLOv5 model exemplifies the impact of AI on early disease diagnosis. Optimized for field conditions with varying light and background complexities, this model has demonstrated an average precision of 86.5% for powdery mildew and 86.8% for anthracnose in rubber trees. Such precision allows for timely and accurate interventions that prevent the spread of diseases [61,62]. Similarly, the integration of AI and robotics in Agriculture 5.0 facilitates the early detection of diseases through drones and ground-based sensors, further enhancing the precision and timeliness of interventions [63].

Beyond specific examples, AI applications extend to various crops, including rice, cucumbers, and apples, where early identification capabilities have proven highly effective. For instance, AI models have accurately detected and classified rice diseases like rice blast with over 95% accuracy, enabling timely interventions that support sustainable farming practices [20].

5.2. Predictive Modeling

5.2.1. AI Models for Predicting Disease Outbreaks Based on Environmental and Biological Data

AI models, and more specifically the ones applying deep learning and machine learning techniques, were developed for disease prediction by analyzing complex environmental and biological data. These models are able to process external data, such as weather conditions, soil health, and crop growth stages, in order to predict potential disease outbreaks. For example, the combination of CNNs and long term memory (LSTM) networks has proved to aid in proactive disease management strategies. More specifically, based on sequential environmental data, it is able to provide early warnings in plant disease prediction, significantly reducing their spread and minimizing crop loss [12].

AI models, such as those using few-shot learning (FSL) and vision transformers (ViT), show particular effectiveness in predicting disease outbreaks, even with limited training data. For example, the PMF+FA method, has demonstrated high accuracy in real-time disease prediction, enabling timely interventions that are crucial for plant health management in dynamic agricultural environments [11].

The integration of these AI models, such as transfer learning and the improved YOLOv5 model, has contributed to the improvement of predictive modeling in agriculture. The YOLOv5 model, for example, utilizes the novel InvolutionBottleneck model not only to achieve increased disease detection capabilities (cf. Section 5.1) but also to handle complex datasets and predict disease outbreaks with high accuracy under natural conditions [61,62]. This model was tested on rubber diseases, where it achieved a mean average accuracy (mAP) of 70%, demonstrating its practical application and effectiveness in real-time disease management [61].

Therefore, predictive modeling using AI becomes essential to predict disease outbreaks in various crops, including corn and wheat. Transfer learning has been particularly effective in adapting models such as ImageNet to agricultural applications where data scarcity is a challenge [20]. These AI-driven models can predict fungal infections in wheat by analyzing weather patterns and soil conditions, thereby enabling more effective application of fungicides and reducing crop losses [63].

5.2.2. Case Studies of Successful AI Implementations in Disease Management

Several case studies have demonstrated the successful implementation of AI in disease management, highlighting the practical benefits of these technologies in real-world agricultural scenarios. For instance, in managing tomato leaf diseases, a combination of Faster R-CNN [66], SSD, and R-FCN architectures was employed to detect and classify lesions with a mean average precision (mAP) of 85.98% [67]. Similarly, a custom deep learning model developed by Li detected five types of apple leaf diseases under natural conditions with an accuracy of 82.28%, outperforming traditional models like YOLOv3 and Mask R-CNN [68].

In another notable case study, the PMF+FA method with vision transformers (ViT) [69] as the backbone for feature extraction was tested on the PlantDoc dataset. This approach outperformed traditional methods, achieving an average accuracy of 90.12%, illustrating the potential of AI in transforming disease management practices, especially in complex agricultural environments [11].

The improved YOLOv5 model has also shown significant effectiveness in disease management. Tested on rubber tree diseases, this model achieved an mAP of 70%, representing a 5.4% improvement over the original YOLOv5 and demonstrating enhanced detection of diseases like powdery mildew and anthracnose. This case study underscores the model's potential for real-time disease management in agriculture, leading to more accurate and timely identification and intervention [61,62].

Additionally, AI-based systems have proven successful in managing pearl millet mildew, where transfer learning with pre-trained models like VGGNet achieved an accuracy of 95% [70]. Another example is the fine-tuning of the InceptionV3 model for disease recognition in various crops, leading to significant improvements in disease management practices [71].

Furthermore, AI systems integrated with UAVs have been effectively used to monitor olive groves for signs of pests and diseases, achieving high accuracy in detecting early infestations. This precise monitoring enabled the targeted application of pesticides, significantly reducing chemical usage and minimizing environmental impact. In wheat fields, AI-driven real-time disease detection resulted in a 20% reduction in yield losses compared to traditional methods, highlighting the substantial impact of AI in enhancing crop health and yield [63].

In Table 7 we summarize the AI algorithms surveyed in this section concerning disease prediction and recognition. For each algorithm, the relevant use cases are listed, and the strengths and limitations for each algorithm are given.

Table 7. AI algorithms used in disease prediction and recognition.

AI Algorithm	Use Case	Strengths	Limitations
Vision Transformers (ViT)	Detect diseases from crop images	Handles large-scale image processing	Requires large datasets for training
LSTM	Time-series analysis for predicting disease progression based on historical weather, soil, and plant health data	Excellent for time-series data, handles long-term dependencies, learns patterns over time	Requires large amounts of data, computationally expensive to train
Few-Shot Learning (FSL)	Detect rare diseases with few samples	Reduces data requirements	Can be complex to train
PMF+FA	Disease detection and crop health prediction	Reduces uncertainty in predictions	May require domain expertise
YOLOv5	Real-time object detection for plant disease	Extremely fast, high accuracy	Trades off some accuracy for speed
Faster R-CNN	Object detection and classification of plant diseases	Accurate for high-quality image classification	Slower compared to YOLO
SSD (Single Shot Multibox Detector)	Image-based disease detection	Fast and efficient	Less accurate for small objects

Table 7. *Cont.*

AI Algorithm	Use Case	Strengths	Limitations
VGGNet	Image-based plant disease classification	Highly accurate, good for transfer learning	Heavy computational load
SVM	Classifying disease symptoms in early stages	High accuracy in small datasets	Requires carefully tuned parameters
PSO-SVM	Hybrid method for disease detection	Combines strengths of both PSO and SVM	Sensitive to parameter tuning
K-Nearest Neighbors (KNN)	Predicts disease spread based on nearby crops	Simple, interpretable	Not scalable to large datasets
ANNs	Disease detection and yield forecasting	Good for non-linear relationships	Prone to overfitting with small datasets
CNNs	Detecting diseases in crops via image analysis	Very effective for image-based tasks	Needs large, labeled datasets
R-FCN (Region-based Fully Convolutional Networks)	Image segmentation for disease detection	Combines speed and accuracy	Computationally intensive

6. AI in Crop Yield Prediction

6.1. Data-Driven Yield Prediction

6.1.1. AI Algorithms for Predicting Crop Yields Based on Historical Data, Weather Forecasts, and Soil Conditions

AI algorithms, including SVM, random forests, and artificial neural networks (ANN), are developed and utilized to predict crop yields by analyzing various input data such as historical yield data, weather forecasts, soil conditions, and environmental variables. Feature selection methods like the Relief algorithm are employed to identify the most relevant features, which are then processed using linear discriminant analysis (LDA) for dimensionality reduction. This refined data is subsequently processed by models such as PSO-SVM (particle swarm optimizationand support vector machines), KNN, and random forest to enhance prediction accuracy [15,72].

The integration of IoT systems further bolsters predictive capabilities by enabling the continuous collection and analysis of vast amounts of data from sensors and drones. Instruments for the measurement of such key parameters, including soil moisture, temperature, and humidity, are employed alongside multispectral cameras which capture aerial imagery, such as vegetation indices (e.g., NDVI). These models provide an all-round and accurate forecast of crop productivity [16,73] based on real time conditions and historical trends along with various environmental factors.

This combined use of machine learning techniques and IoT-enhanced data collection creates a powerful system that delivers valuable insights to farmers, helping them optimize their agricultural practices for improved yield outcomes [74].

6.1.2. Examples of AI-Based Yield Prediction Models and Their Accuracy

AI models have been shown to provide more accurate crop yield predictions in modern agriculture, and numerous studies have proven the increased effectiveness of these methods. These models include a machine learning package, such as the PSO-SVM, KNN, and random forest components, combined into a fairly elaborate system. The model performs very well in predicting crop type across crops. Through feature selection and extraction, particularly using the Relief algorithm [5] and linear discriminant analysis (LDA), the input data were further refined, resulting in improved model performance. All these models were tested and the best one for yield prediction was likely found to be the PSO-SVM, followed by the KNN, due to the high sensitivity value they showed, indicating strong potential for use in agriculture [15].

In addition to the aforementioned approaches, the integration of IoT-based systems has further upgraded the predictive capabilities of AI models. Additionally, IoT systems collect information from other sources, such as high-resolution aerial photography and multispectral cameras or satellites. The NDVI and quasi-linear autoregressive models are typical examples of predicting crop yields. This processing was found to be very effective in crops such as winter wheat, where it was found to achieve high accuracy, especially when processing time series data from different stages of the growing season at the same time. By continuously monitoring crop health and environmental conditions through IoT devices, such as soil moisture sensors and temperature gauges, these AI models are found to provide real-time insights and adjustments, and therefore significantly enhance the overall accuracy of yield predictions [16].

Furthermore, AI-driven models supporting predictive analytics may combine real-time inputs with historical data, to further enhance yield forecasting accuracy. These models use advanced image recognition techniques which enable the continuous monitoring of crop status and health and are able to detect adverse developments, including the lack of nutrients or pest infestations, at an early stage. This is a crucial task, since it enables farmers to take actions to minimize potential losses, which results in crop yield prediction. Additionally, in order to further enhance crop prediction, these models are able to analyze the complex interplay of various factors, including soil quality, weather patterns, and crop growth stages, in order to optimize agricultural practices such as irrigation and fertilization. The predictions of these AI models have been found to be closely aligned with real yields (based on multiple case studies), validating their predictive accuracy, as well as their reliability and practicality in real-world agricultural settings [73].

In conclusion, the integration of AI and IoT into crop yield prediction represents a major advancement in agricultural technology. These systems combine machine learning algorithms and near real-time data collection to deliver actionable information for decision making that is both timely and highly accurate. This not only helps in utilizing the resources to be chosen wisely but also assists decision management concerning the planting, harvesting, and marketing of crops, leading to enhanced productivity and profitability.

In Table 8 we summarize the AI algorithms surveyed in this section in relation to crop yield prediction. For each algorithm, the relevant use cases are listed, and the strengths and limitations for each algorithm are given.

Table 8. AI algorithms for crop yield prediction.

AI Algorithm	Use Case	Strengths	Limitations
LSTM	Time-series analysis for predicting crop yields based on historical weather, soil, and plant health data	Excellent for time-series data, handles long-term dependencies, learns patterns over time	Requires large amounts of data, computationally expensive to train
Random Forest	Yield prediction based on historical data	High accuracy, interpretable	Data-hungry, sensitive to data quality
SVMs	Yield prediction	High accuracy, works well for small datasets, effective in high-dimensional spaces	Computationally expensive for large datasets, difficult to interpret
PSO-SVM	Forecasting of yields considering past data and environmental parameters	Combines strengths of both PSO and SVM	Sensitive to parameter tuning
KNN	Estimation of yield	Simple, interpretable	Not scalable to large datasets
ANNs	Yield forecasting	Good for non-linear relationships	Prone to overfitting with small datasets

6.2. Integration with Market Data

6.2.1. The Role of AI in Linking Yield Predictions with Market Trends and Prices

The potential of AI in agriculture is not limited to traditional yield forecasting, but it also impacts the financial aspects of the agricultural sector, by incorporating market trends and price forecasts into the decision-making process. By using yield predictions, AI helps align agricultural production with market needs, which is beneficial not only for enhancing market efficiency, but also for optimizing pricing strategies. AI gives farmers the ability to make more informed decisions about planting and harvesting schedules, while at the same time allowing them to develop targeted marketing strategies for different crop varieties by providing them with a deeper understanding of the market. This approach ensures that production is both maximized and strategically planned to meet market needs, hence reducing market fluctuations and price volatility risks.

These capabilities are enhanced further by the use of integrated frameworks which combine AI models with IoT systems, since such frameworks are able not only to predict crop yields, but also to provide detailed predictions of future market trends and price movements. Furthermore, these AI models combine a wide range of factors, such as production costs, market demand, and external economic conditions, in order to estimate future crop prices with high accuracy. For example, Sameh et al. [16] present a framework which uses AI-based performance predictions combined with current and historical market data in order to predict future prices. This key feature allows farmers to strategically plan their sales and marketing efforts, ensuring that they can maximize their profits by taking advantage of current market conditions.

In addition, with the use of AI models, which are able to analyze historical pricing data, market trends, and projected returns, farmers can safely navigate volatile markets, where prices can change rapidly due to supply and demand changes. Furthermore, farmers can also make strategic decisions, aligning their production with market conditions, thus enhancing their competitiveness and profitability. For example, AI can suggest that farmers delay a harvest and/or store products until market conditions improve in times of expected oversupply, and thus avoid low market prices and potential financial losses [73].

Using AI for financial planning aspects of agriculture enables the sector to bring in more productive farming practices. AI systems link yield forecasts with financial data, which enables farmers to plan the growing season and post-harvest, in such a manner that every step, from planting to marketing, is optimized in order to maximize the possible output. This solution is particularly useful in highly volatile markets that are very sensitive and where small fluctuations in supply can lead to significant price changes. The ability of AI to analyze large amounts of data and accurately predict outcomes enables farmers to stay ahead of market trends and take proactive measures that ensure their operations remain profitable and sustainable.

By providing accurate and timely information on expected yields and market conditions, AI helps stabilize supply chains while ensuring that both producers and consumers benefit from a more balanced and predictable market. This contributes to improving the efficiency of agricultural markets, but also to food security by ensuring that crops are available when and where they are needed most. It also helps policy makers and agribusinesses to anticipate market trends and design interventions that support both producers and consumers, ultimately leading to a more resilient and sustainable agricultural sector.

In conclusion, incorporating AI into agriculture goes beyond enhancing crop yield predictions. It is fundamentally transforming the way farmers interact with the market. As AI technology continues to evolve, it is easy to conclude that its role in connecting agricultural production with market dynamics will become increasingly critical, driving the future of smart and financially resilient agriculture [15,16,73].

6.2.2. Impact of AI Predictions on Decision-Making for Farmers and Stakeholders

AI-based forecasting has a profound impact on the decision-making processes of farmers and agricultural stakeholders by providing accurate and timely information that enables farmers to make well-timed, informed decisions on crop selection, planting schedules, and necessary inputs to maximize performance. For example, by providing advance forecasting with potential returns, farmers can redesign their resource allocation, optimize planting and harvesting times, and ensure they use inputs such as water and fertilizers efficiently. This precise design not only boosts productivity but also reduces waste, contributing to more sustainable farming practices. By providing personalized recommendations based on each farm's specific conditions, AI helps farmers improve profitability while enhancing sustainability [16].

Furthermore, as mentioned above, the impact of AI-driven forecasting extends beyond individual farms to include wider agricultural actors such as agribusinesses and policy makers [75]. These stakeholders can use the insights generated by the integration of AI to better manage supply chains, predict market trends, and design future agricultural policies. For example, accurate yield forecasts help agribusinesses secure contracts and negotiate better prices, while policymakers can use this data to design interventions that mitigate the risks associated with crop failures. This integrated approach ensures that the entire agricultural sector benefits from improved planning and decision-making processes, leading to a more resilient and efficient food production system.

7. AI in Price Prediction

7.1. Importance of Price Prediction in Agriculture

Price prediction plays a critical role in ensuring economic and social stability, particularly in agricultural markets. Frequent and abnormal fluctuations in the prices of agricultural products can have far-reaching consequences, leading to widespread public concern, impacting people's livelihoods, and even potentially causing social unrest [19]. For countries with large agricultural sectors, such as China, predicting price trends is essential not only for market stability but also for the overall economic health of the nation. The capability to forecast prices accurately plays a crucial role in avoiding conflicts in market prices and—more generally—supporting the smooth operation of the markets.

Additionally, price prediction is a key tool for achieving balanced supply and demand in the agricultural value chain. Taking into account that prices may exhibit high volatility, which can place high pressure on either the producers or the consumers, accurate forecasting allows for taking timely actions that promote market stability and can alleviate the impact, protecting the interests of both producers and consumers. The importance of accurate price prediction is especially important in the following contexts:

- in regions where agriculture is a major area of economic activities, since price volatility may lead in major economic disturbances [76].
- for the protection and enhancement of the income of smallholder farmers. This class of farmers can be supported in making better-informed decisions regarding the selling of their yields, choosing sale periods in which prices are bound to be higher while avoiding sale periods with reduced prices, and achieving higher resilience against adverse market fluctuations [77].

Besides its role in ensuring smooth market operations, accurate price prediction also contributes to ensuring food security. Towards the goal of food affordability and availability maintenance, governments and national/international organizations may utilize price predictions to identify indications of potential price surges in a timely fashion and arrange for suitable interventions [78].

Taking into account the context of global challenges, including population growth (which leads to increased food demand) and climate change (which increases the volatility of crop yields), the role of reliable price forecasting in ensuring a stable and secure food supply [79] is further stressed.

7.2. AI Techniques Used in Price Prediction

Machine Learning Models

Initial attempts at price prediction in agriculture utilized traditional machine learning models, such as linear regression, SVM, anddecision trees. However, the accuracy that can be achieved by these models is hindered due to the overall complexity and the high dimensionality of agricultural data. In particular, while these models have the advantages of simplicity and interpretability, their capabilities of capturing the complex, non-linear relationships that are inherent in agricultural data have been proven limited. Consequently, researchers resorted to more advanced models, such as neural networks [80].

Machine learning models like ARIMA have been successfully combined with SVM [81] or decision trees to tackle these shortcomings through the hybrid modeling [82] approach. Additionally, deep learning techniques, such as LSTM and RNN, allow for the successful modeling of both linear and non-linear components of agricultural price data, including sequential dependencies and complex temporal patterns [36,83], and therefore achieve improved accuracy levels [84,85]. Radial basis function (RBF) models have demonstrated increased capabilities to adapt to specific features of agricultural products and supplies, formulating predictions of high accuracy [19]. LSTM networks are especially well-suited for handling sequential data, making them highly effective in predicting agricultural prices where patterns are often influenced by seasonal trends [86].

In [87], the authors explore multiple models for predicting prices for agricultural supplies and products, and assert that random forest and neural networks exhibit the best performance; price predictions formulated by neural networks exhibit an average deviation of 6.6%, while the respective predictions formulated by random forests exhibit higher deviations, 9.8% on average).

Hybrid models combining machine learning and econometric techniques have also been developed, achieving high forecasting accuracy, especially in contexts with high complexity, in which individual models fail to capture the influence and interdependence of the factors. For instance, decomposition-combination models initially dissect complex data point sequences into smaller components, and then process these smaller components to generate partial predictions, which are integrated to formulate the final prediction [88]. The VMD-SGMD-LSTM model is an example of a hybrid approach that decomposes data into simpler components before applying deep learning techniques, resulting in higher prediction accuracy [76].

Having been trained on extensive datasets, these hybrid models have demonstrated high accuracy in predicting the prices of vegetables in local markets; in some cases, the performance of these models surpasses the performance of econometric approaches [77,80]. The use of genetic algorithms to optimize the performance of traditional machine learning models such as SVM and Bayesian Networks has been also proven fruitful, leading to high accuracy in agricultural product price prediction [79].

7.3. Data Sources for Price Prediction

AI methods for price prediction depend on the existence of accurate and up-to-date datasets, which are used to train the relevant models. Data sources should be comprehensive, comprising the widest possible set of factors that affect prices, as well as the prices themselves. Datasets used for the prediction of price trends are expected to include the following: (a) historical market prices of agricultural data; (b) crop quantity and quality statistics; (c) prices of supplies needed in the agricultural process; (d) demand for agricultural products, which does not only concern the food supply chain but additionally other uses of yields, e.g., biofuel; (e) demand, availability and cost of workforce; and (f) the amount of land that is used for agricultural product cultivation, preferably broken down in subcategories such as arable or irrigable land. The completeness, accuracy, and detail of these data are critical factors to achieve successful AI-based predictions.

Besides factors within the agricultural value chain and the means used therein, supplemental information regarding the environment can play an important role in price prediction. This information includes aspects such as climate and micro-climate type, soil conditions, and weather events. These aspects have a high impact on both the quantity and quality of crop yields, therefore directly affecting market prices; the importance of these data is particularly high in areas with high climate variability and/or intense weather phenomena.

A final set of factors that should be considered in the context of price prediction are related to macroeconomic indicators, such as inflation rates and currency exchange rates. The integration of these factors allows models to capture deeper relationships between agricultural product prices and the economic environment, further elevating prediction accuracy.

Overall, training datasets used for price prediction need to be characterized by two key attributes: (a) comprehensiveness (accommodating factors within the agricultural value chain, the physical environment, and the economic environment); and (b) accuracy and a sufficient level of detail.

7.4. Case Studies and Applications

Prediction of agricultural product prices based on AI models has already been successfully applied in a number of cases. For instance, [19] reports on the use of an RBF neural network model used to predict the prices of garlic and port in China have highlighted its high rate of accuracy and ability to capture short-term price variabilities. Paul et al. [77] present hybrid AI models that can be used for predicting the prices of crops including wheat, rice, and sugarcane; these models exhibit higher performances compared to statistical methods and enable farmers to increase their profits.

Jaiswal et al. [89] present an RNN-LSTM hybrid model that has been applied to predict the prices of wheat and maize, as well as other agricultural products. Especially in areas with high seasonal variability, the application of these models has shown strong potential to lead farmers to better marketing decisions. Furthermore, Vinson et al. [90] present a model based on the generalized regression neural network (GRNN) and support vector regression (SVR), which can successfully predict the prices of fresh foods—especially fruit.

7.5. Challenges in Price Prediction

As noted in Section 7.4, accurate prediction of agricultural product prices necessitates the availability of comprehensive and accurate datasets; this may constitute a challenge, especially in less developed regions, where data availability is reduced [79]. Two more aspects that are inherent to AI models should be catered for, namely the need to (a) capture all factors and their interdependencies and (b) avoid overfitting.

The application of more complex and sophisticated algorithms may lead to more accurate predictions, but these predictions have low interpretability, which leads to lower trust and reduced acceptance potential. This highlights the need for more explainable and interpretable predictions, which can be comprehended, interpreted, and trusted by all stakeholders, including farmers, traders, and market analysts [19,78].

Prices are subject to modifications due to external and unforeseeable developments, such as natural disasters or geopolitical events. While this source of unpredictability cannot be mitigated due to its very nature, AI-based models should allow for the quick adaptation of predictions upon occurrence of such events.

As noted above, achieving both high accuracy and high interpretability is a challenging task, since simple and more interpretable models fail to capture all factors and dynamics, thus attaining lower accuracy levels, while more complex models have reduced interpretability. Providing both highly accurate and interpretable/explainable predictions will enable stakeholders to accept price predictions and trust the actionable insights that are offered by AI systems [91]. To the same end, blockchain technologies may be employed, offering a trusted foundation for storing data inputs and outputs in an immutable and verifiable fashion, minimizing the risk of data manipulation and providing tamper-free transcripts of predictions [92].

In Table 9 we summarize the AI algorithms surveyed in this section concerning agricultural product price prediction. For each algorithm, the relevant use cases are listed, and the strengths and limitations for each algorithm are given.

Table 9. AI algorithms for price prediction.

AI Algorithm	Use Case	Strengths	Limitations
ARIMA (AutoRegressive Integrated Moving Average)	Time-series price prediction	Effective for linear data, interpretable	Does not handle non-linear data well
LSTM	Forecasting crop prices based on historical data	Handles long-term dependencies	High computational cost, difficult to tune
VMD-SGMD-LSTM	Hybrid method for price forecasting, improves LSTM performance	Accurate for complex, non-linear data	Complex to implement and maintain
Bayesian Networks	Probabilistic modeling for price prediction	Good for incorporating uncertainty	Requires expert knowledge for setup
RNNs	Time-series forecasting of market prices	Good for sequential, temporal data	Difficult to train on very long sequences
Generalized Regression Neural Network (GRNN)	Fast, accurate price prediction	Works well with small datasets, easy to train	Sensitive to noise in data
Artificial neural networks	Prediction of prices agricultural products and supplies	Captures non-linear relationships	Prone to overfitting with small datasets
Random forest	Prediction of prices agricultural products and supplies	Handles high-dimensional data well, robust to overfitting, interpretable	Requires large training datasets, computationally intensive for large models

8. AI in Logistics

8.1. AI Applications in Optimizing Supply Chain Processes, Including Storage, Transportation, and Distribution

AI applications in agricultural logistics include the integration of IoT sensors for the real-time monitoring of environmental conditions during transportation and storage, ensuring that products maintain their quality. AI algorithms also optimize transportation routes by analyzing factors like weather and traffic, reducing delivery times and operational costs [10]. AI-driven inventory management systems significantly enhance supply chain efficiency by maintaining optimal stock levels and predicting future demand based on historical and real-time data. This optimization ensures that agricultural products are delivered not only at the appropriate times, but also in the right quantities [9]. When combining AI with machine learning and data analytics, real-time monitoring tools, as well as optimization of logistics processes tools, such as storage and distribution, are available. For example, Morales and Elkader [17] present AI systems which are able to optimize transportation routes, reduce travel time, and minimize costs by taking into account traffic, weather conditions, and fuel consumption. Furthermore, the integration of AI with digital twins (DTs) and distributed ledger technology (DLT) enhances decision-making regarding the processes of storage, transportation, and distribution. As a result, AI is able to analyze data from IoT sensors to predict the optimal storage practices and logistics operations in real time [37].

8.2. Case Studies of AI in Reducing Waste and Improving Efficiency in Agricultural Logistics

When applying AI-based systems in cold chain logistics, both temperature and humidity during transportation can be monitored and controlled, significantly reducing spoilage of perishable items, and thus ensuring that products maintain their quality until they reach consumers. By optimizing the timing of harvests and coordinating logistics, AI-driven predictive analytics streamline supply chain operations [93,94]. This reduces the need for excessive storage and prevents spoilage, which results in minimum waste. The application of AI techniques in logistics has significantly enhanced efficiency by using IoT devices which monitor product freshness during transit, ensuring the safe delivery of perishable goods in optimal condition and reducing spoilage waste. Monitoring the freshness of agricultural products in transit helps to reduce waste by rerouting shipments with real-time data processing and predictive analytics [95]. By implementing this type of systems, not only is the transparency enhanced, but the possibility of disruptions is also reduced (Convergence of Distributed Ledger Technologies).

8.3. AI Tools That Help Farmers Access the Market, as Well as Price and Demand Forecasting

AI-driven platforms directly connect farmers with buyers, bypassing traditional intermediaries. In order for these platforms to predict market demand and set competitive prices, and thus help farmers to maximize their profits, they use advanced AI techniques. The direct connection between farmers and consumers/retailers ensures a streamlined supply chain, as well as better market access. AI-based platforms make market access a lot easier, by providing advanced features, such as price prediction and demand forecasting, etc. These platforms enable farmers to adjust their production strategies based on market trends, thereby reducing the risk of overproduction, and ensuring that they can sell their products at optimal prices. AI tools are indispensable for market access, offering precise demand forecasting and price prediction. By integrating with blockchain technology, these AI platforms ensure secure and transparent transactions, which helps build trust between farmers and buyers (Convergence of Distributed Ledger Technologies) [37].

In Table 10 we summarize the AI algorithms surveyed in this section concerning logistics in the agricultural sector. For each algorithm, the relevant use cases are listed, and the strengths and limitations for each algorithm are given.

Table 10. AI algorithms for logistics in agriculture.

AI Algorithm	Use Case	Strengths	Limitations
SVM [96]	Classifying logistics routes for efficiency	High accuracy for classification tasks	Not scalable to large datasets
Reinforcement Learning (RL) [97,98]	Dynamic routing optimization for minimizing waste	Adapts to real-time changes, learns optimal behavior	Needs continuous retraining, computationally expensive
Artificial Neural Networks [99,100]	Predicting market demand for crops	Handles complex relationships	Requires lots of data, may overfit
Deep Learning (CNNs) [101,102]	Product classification and sorting in packaging centers	Very effective for image-based sorting	High training cost, increased need for labeled data

9. Challenges and Limitations

9.1. Technical Challenges

The success of AI-driven smart farming heavily depends on the quality of data collected from various sensors, drones, and IoT devices. However, data inconsistencies, inaccuracies, and gaps can significantly hinder the performance of machine learning models. The variability of environmental factors such as weather, soil conditions, and crop types necessitates highly adaptive and context-sensitive algorithms, which are complex to develop and fine-tune [103].

Moreover, the high computational power required to process large datasets from UAVs and other sensors remains a hurdle, especially in real-time applications. The integration of these AI tools with traditional farming systems is often hampered by the lack of standardized platforms and interoperability issues [104].

AI-based land use planning tools, while highly effective, also face technical challenges. The integration of topographical data with AI-driven models to simulate various weather scenarios and predict the most suitable areas for crop cultivation requires sophisticated machine learning algorithms, which are computationally intensive and require robust infrastructure that may not be available in all agricultural settings. The algorithms used in AI systems require substantial computational resources and advanced infrastructure, which are often unavailable in rural agricultural settings. The integration of AI tools with existing agricultural management systems also poses challenges, as most current systems are not designed to accommodate the complexities of AI technologies [105].

9.2. Economic and Social Barriers

The cost of AI technologies, including the hardware, software, and training needed to effectively utilize these tools, is often prohibitive for smallholder farmers. This high cost is a significant deterrent to widespread adoption, particularly in regions where agriculture is dominated by small-scale operations [106].

Rural areas are challenged by (a) limited internet connectivity and (b) reduced digital literacy, as compared to large cities. These two factors constitute barriers to the uptake and use of AI technologies. In turn, this further aggravates the gap between technologically savvy farmers (typically including large farms) and those with limited digital skills. These issues must be resolved to allow all farmers to gain access to tools that support advanced and efficient farming operations [105,107].

This digital divide extends to the availability of AI-driven tools for resource management, which are only accessible in a subset of farming installations, typically those where considerable capital investments in advanced technologies can be made [8]. Again, the lack of the potential to use advanced tools widens the gap between farmers that are able to uptake AI tools and farmers that are not.

9.3. Ethical Considerations

The ethical concerns around the deployment of AI in agriculture are related to data privacy, job displacement, and the transparency of AI systems. The large-scale generation and exploitation of agricultural data induces significant privacy concerns, particularly in terms of ownership or such information and considering who has permissions to share it [108,109].

The use of AI to automate farming activities may also have potential impact on the workforce in rural areas, especially in ones where large portions of the population are engaged in agriculture. Displaced workers should be offered the possibility to re-train and re-target their professional careers; allowances may need to be allocated to support workers during the re-targeting period, in order to avoid abrupt socio-economic changes.

Currently, many AI systems operate as “black boxes”, offering results that are difficult to interpret and associate with input data. This may constitute a barrier that limits the uptake of AI-based systems or the adoption of the suggestions they offer; consequently, the aspects of explainability and interpretability of AI systems need to be strengthened.

Further, the use of AI-based in land use planning and crop selection gives rise to ethical concerns about algorithmic bias and overall fairness of AI-provided land use planning. These tools generate recommendations based on their training datasets, and these datasets may be compiled in such a way that some choices are over-represented while others are under-represented. As a result, the algorithm will have a tendency to generate proposals where the former class of choices is more prevalent, effectively marginalizing plants in the latter class and hindering biodiversity [7].

Addressing ethical considerations is vital for the responsible and fair deployment of AI in agriculture. Developing AI technologies that are transparent, inclusive, and context-sensitive, as well as responsive to the socio-economic environments within which they operate, is of high importance to ensure cooperation by stakeholders and enable them to build trust towards AI-based systems [18].

10. Future Prospects and Innovations

10.1. Emerging Trends

10.1.1. Advancements in AI and Combination with Other Technologies

AI has already demonstrated a substantial impact in the agricultural value chain, exploiting advancements in deep learning, as well as technologies like blockchain, IoT, and robotics. Deep learning techniques, such as CNN and RNN, are used to detect crop diseases and predict yield. The integration of blockchain technologies with AI can offer a secure and transparent platform on which input data utilized for model training, as well as results and predictions, can be stored, increasing trust and neutralizing fraud threats.

In conjunction with IoT devices that gather rich and ongoing data on the weather, soil traits, crop health etc., AI algorithms can be fed with real-time data streams of information, which can then be analyzed to provide stakeholders with actionable insights, further supporting process efficiency throughout the agricultural value chain [2,18].

Using the data acquired from NDVI and satellite sources to plan crop rotation with AI enhances predictions of optimized sequences, achieving soil quality improvement and ultimately improved yield, while minimizing environmental consequences [1].

In addition, multi-layer perceptron (MLP)-based neural networks, coupled with real-time, IoT-sourced data streams, offer potential for evaluating land suitability for agriculture. Using these models, land suitability is divided into different types to perform automatic data collection and provide a more accurate and efficient performance for different agricultural operations [43].

Further potential can be identified in the field of weeding devices. Currently, these devices utilize neural networks for weed detection and mechanical systems that can apply the appropriate amount of pesticide to increase precision in eradication and decrease greenhouse-gas emissions [5]. Advancement in detection algorithms can allow the use of weeding devices in cultivations where the error margin for weed detection is currently high due to the similarity between cultivated plants and pests. More generally, machine vision systems in AI-driven robotics can be applied in crop monitoring, weeding, and harvesting, promoting automation (and thereby minimizing labor needs) while reducing the use of chemicals, and ultimately increasing sustainability [110].

Considering the use of AI in resource management, the incorporation of high-order linear models, i.e., LSTM and extreme gradient boosting (XGBoost), into irrigation systems has proven effective for computing the optimal water quantity to be administered during irrigation. These AI models are fed with IoT-sourced data streams, which provide information on soil moisture, weather and solar radiation, and formulate optimal irrigation scheduling policies that maximize crop yields, utilizing available resources efficiently [111].

AI-powered plant disease detection and classification has been applied with satisfactory results in a number of cases [112,113]. CNNs can be utilized for early diagnosis of plant diseases, while transfer learning can be used in order to capitalize models that have been developed for particular plants and/or locations to detect specific plant diseases either (a) on different plant types or (b) on the same plant types, cultivated in different locations or conditions. Still, models trained for specific plant types, locations, and conditions are considerably more efficient than transfer learning-based models or generic models. The creation of models that would provide high detection efficiency without the need for training with data for specific cultivations and identical (or similar) conditions would enable the direct application of models to any type of cultivation.

In the domain of agricultural products price prediction, enhanced RBF neural networks support complex conditions such as those characterizing by agriculture markets and assist more accurate decisions about production and market strategies [19]. The widening of the factors that are taken into account and the development of algorithms that can rapidly adapt to unforeseen developments (e.g., natural disasters) are two indicative directions that will be pursued in this area.

For many aspects of logistics and supply chain management (L&SCM), AI-driven models can optimize transportation routes by taking advantage of technologies such as generative adversarial networks (GANs) and reinforcement learning, achieving reduced costs and also limiting environmental impact [9]. In parallel, IoT sensors can provide real-time information on the condition of the merchandise, supporting the appropriate conditioning of the environment during transportation.

10.1.2. Use of AI in Sustainable Agriculture and Addressing Global Food Security

AI makes a fundamental contribution to the solution of global food security through agricultural practice optimization. In this context, machine learning algorithms process historical data and weather patterns to propose the most suitable crops or crop mixtures that should be planted, resulting in high-value yields and ensuring food security. Such systems also help reduce the effects of climate change in agriculture; they provide predictions on adverse weather, thereby suggesting several adaptive farming schemes. These systems aid sustainable agriculture by optimizing the use of resources, mitigating environmental impact, and enhancing crop productivity [1,2,7]. Land use optimization and crop selection necessitate the application of advance predictive modeling, especially in arid regions; AI plays can be a key driver for the implementation of relevant tools and the formulation of successful recommendations. AI can help farmers to optimize yields and use resources effectively by processing real-time data sourced from IoT sensors and offering actionable insights to stakeholders [43].

The crop yield prediction frameworks, built on advanced machine learning algorithms, help create a system that provides accurate and timely predictions of agricultural output. These technologies are especially critical in areas where agriculture is highly vulnerable to volatile weather and scarce resources. AI systems combine data on the environment with predictive analytics to help optimize the use of water, fertilizers, and other inputs, making agriculture more sustainable and less wasteful and allowing food production to better support global growth.

10.2. Policy and Regulation

10.2.1. The Role of Governments and International Organizations in Fostering AI Adoption in Agriculture

The promotion and uptake levels of AI in the agricultural value chain are moderated, to a large extent, by activities organized by governments and international organizations. These bodies provide funding to support research and development, create infrastructure for precision agriculture, raise awareness of the benefits of the use of AI in the agricultural value chain, and provide incentives for investment in the use of AI, notably through support to public-private partnerships that act as a catalyst for the adoption of AI. Finally, these bodies accelerate knowledge exchange between stakeholders in different countries and/or stages within the agricultural value chain, while also formulating global standards to promote cooperation, innovation, interoperability, transparency, comparability, and consistency [114,115].

Government involvement is particularly important for areas where agriculture is the main economic activity or is deemed critical for ensuring food security. Government intervention can also regulate issues related to the accountable and ethical use of AI-based tools, and ensure access to AI technologies to a wide range of stakeholders.

10.2.2. Recommendations for Policies to Support AI Innovation and Address Challenges

AI is a powerful and invaluable tool for the agricultural value chain, yet a number of issues including data privacy, inequitable access to AI tools, and ethical and responsible use of AI need to be considered. To this end, governments and regulatory bodies need to create and operationalize rules and guidelines for the use of AI in agriculture that safeguard stakeholders' privacy and ensure responsible and ethical use of AI's potential. Moreover, open data repositories may be created and populated, facilitating collaboration and open innovation.

Raising awareness and promoting digital literacy among stakeholders throughout the agricultural value chain is another intervention area for governments and bodies. In this line, farmers can be informed regarding the potential benefits of AI technologies, and training sessions can be organized to elevate digital skills and use of specific AI-based tools. Incentives can be also provided to allow low-income farmers to invest on AI technologies [116]. Unions and cooperatives may also contribute towards this goal.

Lastly, establishing public-private partnerships can be a key factor in driving the adoption of AI technologies in agriculture. Governments and international organizations also have a role in supporting partnerships between AI developers, agronomists, and farmers to design AI models and algorithms according to the conditions of each agricultural environment. Through these partnerships, it will be possible to accelerate AI adoption, overcoming barriers, increasing innovation, and contributing to sustainable farming practices and global food security [117].

11. Use Cases

In this section, we present use cases of real-world applications, which have utilized AI algorithms in order to support and optimize different phases of the agriculture value chain. These use cases demonstrate the value and potential of AI algorithms in precision agriculture.

Pereira et al. [118] report on a progressive web application (PWA) designed to detect plant diseases, utilizing CNNs. The application was deployed and used in India, providing an accessible and effective tool for farmers who may lack technical expertise or consistent internet access, which is often necessary for diagnostic tools. Two CNN architectures were investigated for this application: AlexNet, which was trained from scratch on a dataset of diseased and healthy crop leaves, and ResNet50, which was implemented using a transfer learning approach with pretrained weights. ResNet50 outperformed AlexNet, achieving a validation accuracy of 96%, compared to AlexNet's 84%, largely due to ResNet50's deeper architecture and the use of skip connections, which mitigates performance degradation in deep networks. The application was built using ReactJS and the TensorFlow.js library—with the model stored locally using IndexedDB, an API that allows for user-side storage—to ensure offline functionality, addressing connectivity issues which commonly arise in rural areas. When users upload or capture an image of a plant leaf, the application processes it, normalizes the image, and displays the top five predicted diseases, with the result with the highest confidence first. This system design optimizes usability and accuracy for users with limited technology knowledge. To improve the robustness and usability of the application, proposed updates include training the model on a more diverse set of images that reflect real-world conditions such as different lighting, adding multilingual support for wider regional application, and incorporating disease treatment recommendations. These proposed updates aim to increase the utility and relevance of the tool for end users, ultimately helping farmers manage plant health more effectively.

A smart irrigation system was designed to improve water management in rice fields in Taiwan, where climate change and an aging rural population are exacerbating water shortages [119]. This system incorporates IoT technology to automate and optimize irrigation processes. The system was tested in Tainan City, Taiwan, an area that is representative of the agricultural conditions of most of the country. The system was designed and implemented to monitor environmental conditions (e.g., water levels, weather data) using sensors, adjust irrigation levels based on these measurements, and provide remote access via a cloud-based platform and mobile app. The system is organized into three main components: (a) a sensing layer with sensors to collect real-time data on water level and weather; (b) a network layer that transmits data using NB-IoT, which is a low-power network; and (c) an application layer that allows remote monitoring and control via mobile devices. The system enables farmers to manage water levels remotely. The system was implemented with three irrigation methods: the traditional continuous flooding (CP) method and two modified methods (MCP1 and MCP2), which alternate flooding and drying to reduce water needs. The results showed that MCP1 and MCP2 achieved significant water savings, with rates of 2.9–18.7% during the dry season and 8.8%-19.3% during the wet season. Importantly, this water saving did not negatively affect crop yields or agronomic characteristics. In fact, the MCP methods resulted in equal or better yields in some cases, highlighting the feasibility of reducing water use without sacrificing productivity. Future recommendations include incorporating more advanced artificial intelligence and big data methods into the system, to further improve predictive irrigation strategies and potentially increase yield. This intelligent irrigation system therefore holds promise for addressing water scarcity and labor challenges in Taiwanese agriculture, offering a model for sustainable water use in other regions facing similar challenges.

Qaswar et al. [120] report on the use of AI-based methods to optimize the use of nitrogen fertilizers in potato cultivation. Given that excessive nitrogen (N) application is common in agriculture, especially in nutrient-demanding crops such as potatoes, the work in [120] seeks to tailor nitrogen application to specific areas, potentially reducing input costs and environmental impacts, while maintaining or increasing crop yields. The method was applied in a commercial potato field in Belgium, where soil properties such as moisture, pH, total organic carbon, and other nutrients were mapped using visible and near-infrared (Vis-NIR) spectroscopy. These data were combined with vegetation indices from Sentinel-2 satellite images to define fertility-based management zones (MZs), which were categorized as high (VR-H), medium-high (VR-MH), medium-low (VR-ML), and low fertility (VR-L). The demarcation of management zones was performed using the k-means algorithm, where clustering was based on the predicted soil properties and normalized difference vegetation index (NDVI). Nitrogen application was adjusted according to the individual zone fertility categorization: high-fertility zones received 50% less N than the uniform rate (UR), while low-fertility zones received 50% more. VR-N application showed clear benefits over the UR treatment. The application of this method resulted in an increase in potato yield of 1.89 tons per hectare and improved the relative gross margin by 374.83 euros per hectare. Specifically, the highest yield increase was observed in the medium-low fertility zone (VR-ML), which received 25% more nitrogen than the UR. Environmental analysis showed improved nitrogen use efficiency in variable-rate nitrogen treatments, suggesting that crops used nitrogen more efficiently when application rates matched field variability. However, in the low fertility zone (VR-L), a 50% increase in N did not significantly enhance yield, indicating reduced yields at higher levels of nitrogen input in less fertile areas. The same study reports on the development of Vis-NIR calibration models for soil MC, pH, TOC, P, K, Mg, Ca, and cation exchange capacity (CEC), using partial least squares regression (PLSR). The authors of [120] suggest that further improvement of decision-making for nitrogen application in specific zones is feasible through the incorporation of nitrogen mineralization rates and historical crop yield. This could help prevent excessive nitrogen application in zones where increased fertilizer use is not associated with yield benefits. The work in [120] demonstrates the potential of AI-based precision agriculture technologies to increase profitability and reduce environmental impacts, demonstrating a strong case for VR-N as a sustainable solution in intensive potato cultivation.

Pang et al. [121] report on a random forest regression (RFR)-based application to predict wheat yields at both regional and local scales in southeastern Australia, encompassing paddocks in Victoria, New South Wales, and South Australia. The application uses high-resolution normalized difference vegetation index (NDVI) data obtained from PlanetScope satellite imagery, combined with meteorological data, to develop data-driven, scalable models for yield prediction. The RFR model provides valuable insights for precision agriculture, particularly for making informed decisions about variable rate fertilization, irrigation, and resource management, thereby enabling early in-season yield estimates. For local predictions, the RFR model combined data across all paddocks, achieving high prediction accuracy (R^2 = 0.86, root mean square error (RMSE) = 0.18 tons per hectare (t/ha)). At the local scale (individual paddock), the model performed best in Victoria (R^2 = 0.89, RMSE = 0.15 t/ha) and New South Wales (R^2 = 0.87, RMSE = 0.07 t/ha), with moderate performance in South Australia (R^2 = 0.45, RMSE = 0.25 t/ha). The differences in accuracy between regions are attributed to variations in soil characteristics, topography, and crop variety, which increase yield prediction complexity. Feature importance analysis identified NDVI data as the most critical for accurate yield predictions. These time-related insights reflect the relationship between maximum biomass and final yield, particularly during sensitive growth stages; on the contrary, meteorological variables were found to contribute little to the model performance, suggesting that NDVI adequately captures plant health and growth conditions under non-extreme environmental conditions. Future research may enhance the adaptability of the model by incorporating additional vegetation indices, such as chlorophyll content indices, which may offer improved yield sensitivity. It is also suggested that the approach be extended to other growing seasons and additional paddocks to test its robustness under different climatic conditions. The research in [121] asserts that RFR models operating on top of large datasets offering diverse feature selections, which are sourced from satellite imagery and IoT devices, can be successfully deployed for operational, spatially detailed wheat yield predictions, effectively supporting farmers in the context of the precision agriculture value chain.

12. Discussion

The agricultural value chain comprises multiple stages, including the planning of field use, sawing, cultivation, disease prevention, detection and treating, processing, storage, transportation, and distribution of agricultural products. Each of these stages is inherently complex and requires a substantial amount of expertise, while the diversity and interdependence of these steps introduce additional barriers to the overall optimization of the agricultural processes. AI systems provide a means to formulate optimal agricultural process plans, streamlining the related processes, reducing waste, and improving the value chain efficiency both at the global level and at the individual stage level. To this end, AI technologies are combined with developments in the IoT, robotics, blockchain, and other areas to offer seamless, secure end-to-end solutions that address the needs of all stakeholders.

While significant progress has been achieved thus far and AI-based systems are already employed successfully in a number of cases, further research and development are required to improve existing solutions, promote the integration of solutions concerning different stages of the agricultural value chain, and address newly emerging needs and trends:

- Improved Crop Selection and Rotation Planning: Further enhancement of AI powered models such as gradient boosted decision trees (GBDT) and LSTM networks can offer more successful and targeted recommendations concerning the choice of plants to be cultivated in given fields, across sequences of growing seasons.
- Improved AI-Enabled Robotics: Current developments in the field of autonomous farming robots, which are packed with cutting-edge machine vision and deep learning capabilities, will be advanced to offer higher precision during weeding and harvesting, while still reducing labor requirements and supporting sustainable farming practices.
- Expansion of AI in Agricultural Logistics: The combination of blockchain technology, explainable/interpretable AI, and IoT systems unveils new opportunities for (a) increased transparency in the supply chain, (b) optimization of transportation routes, and (c) potential access to more profitable markets. In this context, waste can be minimized, chain efficiency can be improved, and stronger guarantees can be offered regarding the quality of products reaching the final consumer, while farmers will have opportunities to increase their income. The combination of these technologies can also be a key driver for successful implementation of circular economy principles to the agricultural value chain.
- Addressing Ethical and Social Challenges: Future research has to ensure that AI technologies are transparent, equitable, and accessible for all stakeholders, including those in rural areas or under-privileged contexts. This necessitates the formulation and application of policies on safeguarding data privacy, digital literacy, and reducing the digital divide to ensure that the benefits of AI are distributed more fairly across stakeholders.

Finally, we can gain a more complete picture of the AI algorithms that now enable farmers and those involved in the agricultural sector to use new and continuously evolving technologies. The following summary table serves as a guide, showing the algorithms corresponding to the domains in which they can be applied.

Table 11 summarizes the AI algorithms and the areas of the agricultural sector they can be applied to. Neural network-based algorithms are grouped at the end of the table, to facilitate correlation.

Table 11. Table of AI algorithms and the domains of the agricultural sector they can be applied to.

AI Algorithm	Land Use and Crop Selection	Resource Management	Crop Monitoring and Irrigation	Automated Planting, Weeding, and Harvesting	Disease Detection	Yield Prediction	Price Prediction	Logistics in the Agricultural Sector
Random Forest	✓	✓				✓	✓	
SVM	✓		✓		✓	✓		✓
LSTM			✓		✓	✓	✓	
Gradient Boosted Decision Trees (GBDT)	✓							
Deep Q-Networks (DQNs)	✓							
Dominance-based Rough Set Approach (DRSA)	✓							
Multi-Layer Perceptron (MLP)	✓							
XAI-CROP	✓							
Particle Swarm Optimization (PSO)		✓			✓			
Gradient Boosting Machines (GBM)		✓						
YOLOv5					✓			
Faster R-CNN				✓	✓			
SSD (Single Shot Multibox Detector)					✓			
VGGNet					✓			
Vision Transformers (ViT)					✓			
Few-Shot Learning (FSL)					✓			
PMF+FA					✓			
KNN					✓	✓		
PSO-SVM					✓	✓		
Reinforcement Learning (RL)								✓
Bayesian Networks							✓	
ARIMA							✓	
VMD-SGMD-LSTM							✓	
ANN					✓	✓	✓	✓
Generalized Regression Neural Network (GRNN)							✓	
CNNs		✓	✓	✓	✓			✓
RNNs		✓	✓	✓			✓	
R-FCN (Region-based Fully Convolutional Networks)					✓			

At this point, and based on the preceding analysis, the conclusions related to the research objectives posed in the introduction can be stated as follows:

- RO1. To explore how can AI-based tools improve land use planning and crop selection to enhance agricultural productivity and sustainability.
  AI-based tools improve land use planning by analyzing soil quality, weather patterns, and topography, allowing farmers to make informed decisions about land allocation. Machine learning models like SVMs and decision trees help predict soil health and identify the most suitable areas for specific crops. AI-driven crop selection methods, such as gradient boosted decision trees (GBDT) and regularized greedy forest (RGF), offer more accurate recommendations, optimizing crop selection and rotation planning to maximize yield and sustainability.
- RO2. To identify which are the most effective AI-driven strategies for optimizing resource management, including water use, fertilizer application, and energy efficiency.
  AI-driven strategies optimize resource management by utilizing real-time data from IoT sensors and advanced machine learning models to manage water, fertilizers, and energy efficiently. For instance, AI-driven irrigation systems use soil moisture data and weather forecasts to adjust water distribution, minimizing waste and enhancing crop health. AI models also optimize fertilizer application based on crop growth stages, reducing environmental impact while maximizing yield. In greenhouse operations, AI optimizes energy use by adjusting heating, lighting, and ventilation, leading to significant reductions in energy consumption.
- RO3. To determine and document how AI contributes to precision agriculture, particularly in optimizing planting schedules, irrigation, and crop monitoring.
  AI contributes to precision agriculture by analyzing vast datasets, including historical climate data and real-time weather forecasts, to predict optimal planting schedules. AI-driven systems like those integrated with 6G-enabled IoT networks manage irrigation with precision, ensuring optimal water distribution based on real-time soil and weather data. For crop monitoring, AI models process data from drones and sensors to detect early signs of stress, enabling timely interventions that prevent yield losses and maintain crop health.
- RO4. To highlight the potential benefits of AI in early disease detection and yield prediction, and establish whether these applications can contribute to the mitigation of risks in agriculture.
  AI enhances early disease detection through advanced image recognition systems that utilize CNNs and transfer learning. These systems can identify plant diseases with high accuracy, allowing for timely interventions that prevent crop losses. In yield prediction, AI models analyze historical data, weather patterns, and soil conditions to forecast crop yields accurately. These predictions help farmers optimize their practices and make informed decisions, reducing risks associated with unpredictable weather and resource limitations.
- RO5. To survey how AI can be integrated into agricultural logistics to reduce waste, improve efficiency, and enhance market access for farmers.
  AI can be integrated into agricultural logistics by optimizing supply chain processes, including storage, transportation, and distribution. AI-driven systems monitor environmental conditions during transportation to ensuring product quality, and optimize routes to reduce delivery times and costs. AI platforms also facilitate market access for farmers by providing demand forecasting and price prediction, enabling them to align production with market trends and maximize profitability. The integration of blockchain with AI further enhances transparency and trust in the supply chain.
- RO6. To identify the future prospects for AI in transforming the agricultural value chain, and the challenges that must be addressed to realize its full potential.
  The future prospects for AI in agriculture are promising, with continued advancements expected in areas such as crop selection, robotics, and logistics. However, realizing AI's full potential requires addressing challenges related to data privacy, the digital divide,

and the ethical use of AI technologies. Governments and international organizations must establish supportive policies, promote digital literacy, and ensure equitable access to AI tools. By overcoming these challenges, AI can significantly transform the agricultural value chain, enhancing productivity, sustainability, and food security on a global scale.

13. Conclusions

In conclusion, the future of agriculture depends on the successful integration of cutting-edge technologies, mainly including AI and IoT. This is corroborated through the multiple successful implementations of precision agriculture, which process IoT-sourced data using AI algorithms, providing farmers with actionable insights.

As AI technology continues to evolve, it will play an increasingly critical role in ensuring food security and meeting the global demand for food. However, fully exploiting the potential of AI in agriculture requires addressing technical, economic, and ethical challenges associated with its adoption. With strong support from governments, international organizations, and the private sector, AI has the potential to transform agriculture into a more efficient, sustainable, and resilient industry.

This work lays the foundation for further research and development in expanding the integration of AI, developing new algorithms and improving existing ones, and encouraging interdisciplinary collaboration and innovation.

In addition, the paper examines the integration of AI across the spectrum of smart agriculture, from selecting the right farm, seeds, and the right time to start the cultivation process, to placing the product on the shelf, providing an integrated approach. In doing so, it highlights how advanced technologies can contribute to solving issues throughout the production and distribution of agricultural products, providing a road map for researchers, policy makers, and practitioners to develop and implement effective strategies.

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