sustainability

MDPI

Review

Machine-Learning-Based Frameworks for Reliable and Sustainable Crop Forecasting

Khushwant Singh [1], Mohit Yadav [2], Dheerdhwaj Barak [1], Shivani Bansal [2] and Fernando Moreira [3,4,*]

[1] Department of Computer Science & Engineering, University Institute of Engineering and Technology, M.D. University, Rohtak 124001, Haryana, India; erkhushwantsingh@gmail.com (K.S.); barakdheer410@gmail.com (D.B.)
[2] Department of Mathematics, University Institute of Sciences, Chandigarh University, Mohali 140413, Punjab, India; mohit.e15793@cumail.in (M.Y.); shivanibansal.maths@cumail.in (S.B.)
[3] Research on Economics, Management, and Information Technologies (REMIT), Universidade Portucalense, 4200-072 Porto, Portugal
[4] Institute of Electronics and Informatics Engineering of Aveiro (IEETA), Universidade de Aveiro, 3810-193 Aveiro, Portugal
* Correspondence: fmoreira@upt.pt

Abstract: Fueled by scientific innovations and data-driven approaches, accurate agriculture has arisen as a transformative sector in contemporary agriculture. The present investigation provides a summary of modern improvements in machine-learning (ML) strategies utilized for crop prediction, accompanied by a performance exploration of contemporary models. It examines the amalgamation of sophisticated technologies, cooperative objectives, and data-driven methodologies designed to address the obstacles in conventional agriculture. The study examines the possibilities and intricacies of precision agriculture by analyzing various models of deep learning, machine learning, ensemble learning, and reinforcement learning. Highlighting the significance of worldwide collaboration and data-sharing activities elucidates the evolving landscape of the precision farming industry and indicates prospective advancements in the sector.

Keywords: crop prediction; machine learning; deep learning; smart farming; precision agriculture

check for updates

Academic Editor: Hossein Bonakdari

Received: 24 March 2025
Revised: 29 April 2025
Accepted: 13 May 2025
Published: 20 May 2025

Citation: Singh, K.; Yadav, M.; Barak, D.; Bansal, S.; Moreira, F. Machine-Learning-Based Frameworks for Reliable and Sustainable Crop Forecasting. *Sustainability* **2025**, *17*, 4711. https://doi.org/10.3390/su17104711

1. Introduction

Crop prediction utilizing precision farming is an intellectually stimulating and sophisticated method that corresponds with the advancing agricultural sector [1]. This strategy depends on the meticulous utilization of progressive tools, particularly remote sensing, to assess crop harvests. Its swift rise in the agriculture sector is transforming farming methodologies, offering farmers a data-driven approach that markedly enhances overall productivity [2]. Central to precision agriculture is the utilization of satellite imagery, an effective instrument for producing dynamic vegetation index maps. These maps function as essential tools for facilitating informed decision-making in agricultural activities. The method commences by categorizing these maps into specific zones, each reflecting the well-being prestige of the vegetation. This spatial classification facilitates planned resource allocation and agricultural methodologies. The subsequent procedure entails meticulously gathering crop harvest trials within these areas, closely associated with neighboring vegetation indices. The advancement of intricate yield estimate algorithms is essential for producing accurate projections, signifying a shift from conventional agricultural practices. Agricultural methods signify the diverse techniques and procedures employed in agricultural cultivation and livestock rearing. Conventional techniques encompass crop rotation, intercropping, and the application of organic fertilizers to sustain soil health organically. Contemporary techniques utilize chemical fertilizers, herbicides, high-yield crop types, and mechanical equipment to enhance output. Precision agriculture is an innovative approach that employs sophisticated skills such as sensors, GPS, and data analytics to enhance farming methods and resource utilization [3]. Each method possesses distinct advantages and problems, contingent upon aspects such as scalability, environmental effect, and resource availability. Conventional methods are generally economical and sustainable; however, they may yield lesser productivity in comparison to contemporary, technology-enhanced agricultural practices.

The hallmark of crop prediction via precision farming is its myriad effects. It radically alters the cultivation process by offering a real-time, data-driven approach that optimizes resource allocation, minimizes waste, and, ultimately, improves crop yields. Armed with data-driven insights, farmers may make timely decisions, thus enhancing their productivity and profitability. Moreover, the incorporation of machine-learning and data analytic methodologies expands the potential of crop forecasting. These algorithms adeptly analyze extensive datasets and adjust to changing circumstances, consistently enhancing predictive precision. In this context, machine learning functions as a powerful tool for integrating multi-dimensional data sources, including soil quality assessments, meteorological information, and satellite imagery [4]. The integration of remote sensing and machine learning in precision agriculture and crop forecasting advances science and technology. Researchers in this domain diligently investigate methods to enhance forecast accuracy and cultivate user-friendly interfaces to enhance accessibility for farmers [5]. Crop prediction via precision agricultural represents a compelling area of scholarly investigation and innovation, highlighting the revolutionary capabilities of contemporary equipment in farming. This integration of tools and cultivation is at the vanguard of scientific research, set to transform future farming practices by enhancing efficiency, minimizing waste, and increasing crop yields [6]. Recent developments in large-scale artificial intelligence models, including various AI tools, are catalyzing a substantial revolution in precision agriculture by facilitating more intelligent, efficient, and sustainable farming operations. Such artificial intelligence technologies enable farmers to utilize real-time data analysis, predictive insights, and automated decision assistance for crop monitoring, disease diagnosis, and resource management, leading to enhanced yields and diminished environmental impact. AI-driven systems may assess satellite imagery and sensor data to enhance irrigation and fertilization, identify early indicators of agricultural stress or insect infestations, and predict yields with considerable precision. Autonomous machinery and robots, directed by AI, increase operational efficiency by automating tasks like planting and harvesting. The successful integration of these technologies necessitates overcoming the problems associated with data security, digital infrastructure, and equitable access, particularly for smallholder farmers. The implementation of massive AI models in precision agriculture is transforming the industry, presenting opportunities for substantial developments in productivity, sustainability, and food safety.

A critical analysis of machine-learning techniques, performance evaluation, problems, and prospective developments has been carried out. We performed a performance evaluation of modern machine-learning, deep-learning, reinforcement-learning, and ensemble-learning models for crop prediction; the identification and analysis of the challenges and impediments faced in crop forecasting using precision agriculture methodologies; and an examination of potential future pathways, offering insights and a framework for ongoing research, innovation, and progress in agriculture with precision. The current research primarily aims to investigate and assess resilient machine-learning frameworks tailored for accurate crop production prediction, an essential aspect of precision agriculture. The research focuses on the creation, enhancement, and evaluation of machine-learning prototypes capable of precisely predicting crop yields under diverse environmental conditions. It also examines the adaptation of these models to obstacles such climate unpredictability, data shortages, and varying farming sizes, with the objective of facilitating more informed agricultural decision-making and bolstering the resilience of food production systems.

2. Literature Review

The present investigation carefully analyzed the selected literature on crop prediction and precision farming. The main objective is to unearth new patterns, address relevant concerns, and identify interesting crop prediction and the precision agriculture potential by thoroughly researching these studies. The investigation serves as the foundation for our analysis, helping us better comprehend the current agricultural landscape and the novel farming technologies that are defining the future. An advanced precision agriculture crop recommendation system utilizes data mining to customize crop suggestions based on the soil conditions of Indian farmers [7]. Crop selection is critical in precision farming, according to research. A detailed review of the pertinent studies and classification algorithms establishes a solid research foundation. To elucidate their sources, researchers apply a sophisticated ensemble model as well as soil-specific features. The model's ability to detect illness data is outstanding; however, the crop production forecast is not considered. Khalid et al. investigated the utilization of precision farming methodologies to forecast potato crop production in three wetted areas in Saudi Arabia [8]. The study utilized GIS and remote sensing techniques, including Sentinel-2 and Landsat-8 satellite data to assess tuber crop output. The researchers developed vegetation index maps employing vegetation indices, which were subsequently classified into zones based on evaluations of vegetation health. The development of yield prediction algorithms followed the establishment of stratified random sampling regions, the collection of agricultural yield samples, and their correlation with nearby vegetation indices. The results of the study showed that potato crop production was reliably predicted using precision agriculture techniques, with prediction errors ranging from 3.8% to 10.2% for Sentinel-2 imaging and from 7.9% to 13.5% for Landsat-8 images. The researchers emphasized how these methods may transform agriculture by improving crop management and resource efficiency. Due to the study's narrow emphasis on only three irrigated farms in Saudi Arabia, the findings might not be generalizable to other regions or crops around the world. Thilakarathne et al. developed a cloud-enabled recommendation system that serves as a tool for machine-learning-driven precision agriculture, thereby greatly advancing the domain of precision farming [9]. This cutting-edge platform employs satellite imagery, soil sensors, meteorological stations, and many data sources, all of which can be analyzed through machine-learning methodologies to provide customized crop suggestions for specific farms. Figure 1 depicts the machine-learning techniques for accurate agricultural forecasting. Novel AI techniques are progressively utilized for vegetation forecasting to enhance precision and efficacy. Machine-learning models, including random forests and convolutional neural networks (CNNs), are employed to analyze extensive datasets derived from satellite photography, drones, and field sensors to forecast vegetation growth, health, and distribution. These programs may identify patterns and nuanced alterations in plant conditions that are challenging for people to analyze. Deep-learning methodologies facilitate the forecasting of crop production and the early identification of illnesses or stressors. Integrating AI with real-time environmental data enables researchers and farmers to make more accurate and timely judgments to enhance agricultural operations. The triangle in the middle of Figure 1 indicates the various machine-learning techniques for precise agricultural forecasting such as supervised learning, deep learning, unsupervised learning, and ensemble learning.

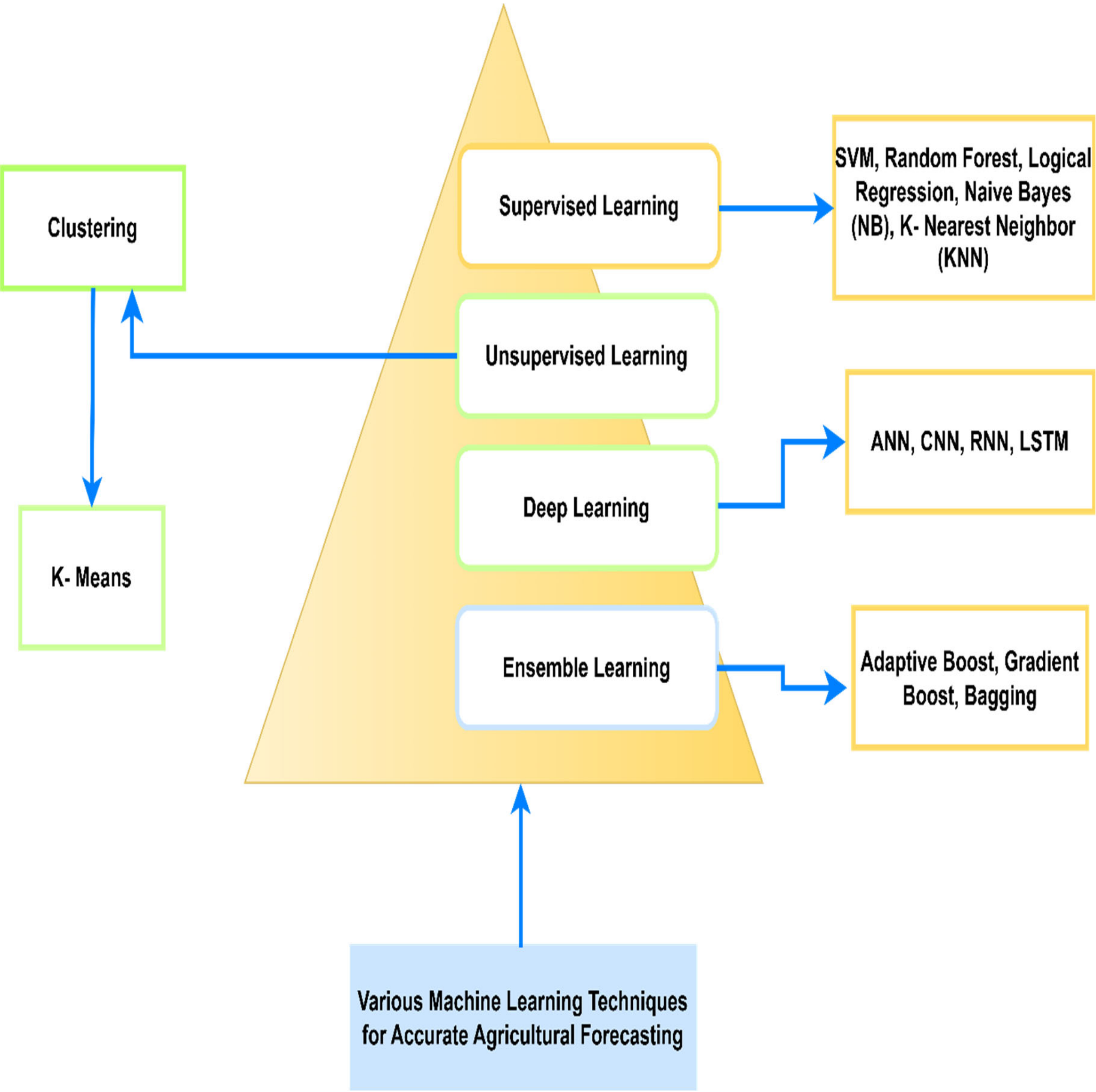

Figure 1. Machine-learning techniques for accurate agricultural forecasting.

Figure 1 illustrates the wide range of machine-learning methodologies frequently employed to enhance the precision of agricultural forecasting. The importance of this work is to provide a systematic summary of essential algorithms—such as SVM, ANN, RF, and deep-learning models—that have been effectively utilized for tasks including crop yield prediction, soil condition assessment, disease detection, and resource optimization in precision agriculture. Figure 1 visually summarizes these methods, contextualizing the technological landscape, illustrating the variety of available approaches, and establishing a basis for subsequent discussions in the research concerning model selection, performance evaluation, and their specific applications to agricultural challenges. Machine-learning algorithms are essential in precision agriculture, facilitating data-driven decision-making to enhance farming techniques. These algorithms examine extensive and intricate datasets encompassing meteorological patterns, soil conditions, crop vitality, and satellite imagery to identify trends and generate precise forecasts. Applications encompass forecasting agricultural production, early disease detection, efficient irrigation scheduling, and pest outbreak prediction. Machine-learning improves agricultural productivity, reduces resource waste, and strengthens the environmental responsibility and resilience of farming practices by evaluating real-time and past information. Yasam et al. [10] thoroughly examine the potential of precision agriculture, highlighting the limitations of conventional farming techniques and emphasizing the benefits of machine learning in crop forecasting, including effective data analysis. The researcher describes the platform's architecture, including data loading, preprocessing, model construction, and generalization phases, as well as its real-time functionalities and intuitive interface. The researchers underscore the need for rendering the technology accessible to farmers, especially in distant areas. Researchers emphasize the significance of ongoing research and development to enhance the precision and efficiency of crop prediction via machine learning. A supervised learning model to forecast the seed germination capacity, an essential component of precision agriculture, has been introduced by some researchers [10]. Researchers underscore the importance of seed germination, critique traditional assessment techniques, and advocate for a machine-learning methodology as a viable alternative. The employed materials and methods are delineated, encompassing the dataset of seed images and their corresponding germination rates, data preprocessing methodologies, and the model architecture, which comprises a convolutional neural network for feature extraction and a multi-layer perceptron for classification. Additionally, explained are performance evaluation measures and hyperparameters. The outcomes, which include noteworthy ablation experiments, demonstrate the model's superiority over conventional techniques. Information and communication technology (ICT) and its revolutionary potential in traditional agriculture were studied by Ayoub et al. [11]. A variety of contemporary technologies, including as robotics, Internet of Things devices, machine learning, and artificial intelligence, are systematically investigated by researchers to determine their applicability to precision agriculture. The researchers examine the challenges associated with the assimilation of various tools, as well as the significant expense of the equipment and the necessary knowledge for an effective process. An overview of the prevailing research is provided, emphasizing the application of machine learning and artificial intelligence in agriculture, specifically in areas such as crop production prediction, soil analysis, and disease recognition. Researchers encompass the deployment of drones for agricultural monitoring and managing, providing insight into the benefits and intricacies of their execution.

Finger, Robert et al. conducted a comprehensive investigation of precision agriculture and its impact on the surroundings and agricultural productivity [12]. Researchers analyzed the latest developments in big data and technology to enhance precision, connectivity, efficiency, and general applicability. Researchers also discussed how PF technologies could be rendered more accessible, hence enhancing their overall beneficial influence on society through improvements in legal and technological frameworks. Researchers delivered a comprehensive study of PF's current status and its capacity to transform agriculture and promote sustainable growth. Researchers provided comprehensions into the mechanisms, applications, drifts, and future possibilities of PF. Furthermore, researchers examined the policy components of PF and their interrelations with additional ecological and agricultural strategies, and provided case studies and instances of successful PF implementation across diverse worldwide locales, acting as a reference for farmers and policymakers. In their analysis of UAV applications in precision agriculture, Dimosthenis et al. evaluated the revolutionary potential of new technologies such as IoT and UAVs for in-the-moment agricultural decision-making [13]. The evaluation included a review of hyperspectral imaging and related techniques, determining which sensors are best suited for which uses. A survey also looked into the application of deep learning to data management [14,15]. The researchers underscored the lack of a literature survey especially addressing prevalent methodologies for the utilization and analysis of UAV imagery in agricultural settings, accentuating its critical importance. Researchers underscored the essential requirement for a consistent workflow, as its absence obstructs the extensive implementation of UAV systems in commercial precision agriculture applications [16,17]. The variation in techniques and methodologies among researchers targeting the same objective may result in inferior outcomes [18,19]. Ahmed et al. present a scalable network architecture that employs fog computing and an extended WiFi network within the IoT for the tracking and overseeing of agricultural and rural farms [20,21]. The suggested method implements a cross-layer channel interaction and routing system for sensing and actuation to alleviate network latency [22]. The researchers utilized testbed experiments and simulations to assess the system's performance [23]. The simulation study was conducted in two phases: The performance of the planned WSN and WiLD network was initially evaluated independently [24]. The overall performance of the framework was subsequently assessed, utilizing the results from the initial phase. The researchers delineated the evaluation methodologies and assessed the architecture's performance in the testbed assessment. Figure 1 depicts several machine-learning methods utilized in precision agriculture for crop forecasting. This encompasses supervised learning techniques and deep-learning methodologies, including RNN and CNN. Ensemble techniques such as gradient boosting and adaptive boosting are also presented.

Diverse applications of machine-learning (ML) techniques in numerous fields of agriculture have been analyzed. Machine learning (ML) has arisen as an indispensable tool in contemporary agriculture, providing solutions to numerous issues encountered by the sector. In agricultural management, machine-learning algorithms are employed for yield forecasting, disease identification, and weed recognition, allowing farmers to make informed decisions and enhance production efficiency. Soil analysis is enhanced by machine learning through the evaluation of soil fertility and moisture content, enabling accurate irrigation and fertilizing techniques. Livestock management employs machine learning to monitor animal health and behavior, hence enhancing welfare and productivity. Moreover, machine learning facilitates resource management by enhancing the utilization of water, fertilizers, and pesticides, thereby promoting sustainable agricultural practices. These applications illustrate the revolutionary effect of machine learning on improving efficiency, productivity, and sustainability in agriculture.

In agriculture, machine-learning techniques are essential for improving decision-making and maximizing resource use. Supervised learning techniques, like random forests and support vector machines, are utilized to forecast agricultural yields and identify illnesses by analyzing labeled datasets that consist of historical yield data, meteorological patterns, and soil characteristics. Unsupervised learning techniques, such as k-means clustering, aid in recognizing intrinsic patterns within unlabeled data, enabling tasks like soil type categorization and the identification of management zones. Deep-learning methodologies, especially convolutional neural networks, excel in analyzing intricate data such as satellite imaging, facilitating precise crop classification and the assessment of vegetation health. Ensemble-learning techniques, which integrate many models, improve prediction accuracy and robustness, demonstrating efficacy in applications such as agricultural yield forecasts and recommendation systems. Such machine-learning paradigms greatly enhance precision agriculture, fostering sustainable and efficient farming techniques.

3. Accessible Datasets for the Public in Crop Prediction

The different public datasets used in crop prediction are shown in this section; certain datasets are accessible upon request. Analyzing the various datasets is essential for comprehending the range of data that goes into making precise agricultural forecasts. These datasets are frequently used by researchers and practitioners to create and evaluate models that take into account variables including soil characteristics, climatic conditions, and past crop performance. As Table 1 illustrates, the quality and accessibility of datasets are crucial factors in crop prediction models, impacting their dependability and regional applicability.

Table 1. Collections of data in the precision agriculture sector [25].

Reference	Purpose/Goals	Year	Method	Numbers of Objects
[26]	Flower Classification	(2006)	Standard Method	1360
[27]	Fruit and Vegetable Categorization	(2017)	Fusion Method	~160,000
[28]	Species Categorization and Detection	(2018)	R-CNN	~6.6 M
[29]	Pest Detection	(2019)	Deep Learning	18,983 images
[30]	Fruit Detection	(2020)	R-CNN	1455
[31]	Pest Detection	(2021)	Deep Learning	~264,700
[32]	Fruit Detection and Tracking	(2022)	R-CNN	~86,000
[33]	Pest Detection	(2022)	AI-based Algorithm	6410 images
[34]	Tree Counting, Disease Recognition, Classification, and Integration	(2022)	AI-based Methods	93
[35]	Grey Mold Recognition	(2023)	Deep Learning	121
[36]	Fruit Recognition and Tracking	(2023)	Object Detection and Tracking Algorithms	~8000
[37]	Grassland Recognition for Farming Robotics	(2023)	Object Detection Algorithms	15,519

4. Analysis of Various Machine-Learning Techniques

4.1. Techniques for Supervised Learning

In the area of precision farming, the use of learning through supervision is well-acknowledged. A number of well-established approaches are included in these methodologies, each of which makes a distinctive contribution to the field. The supervised learning methods that are widely used and widely deployed include linear regression (LR), support vector machines (SVMs), k-nearest neighbors (KNN), naïve Bayes, and random forest. In terms of decision boundaries, SVM shines, while linear regression (LR) is proficient in modeling probabilities, k-nearest neighbors (KNN) relies on closeness for categorization, naïve Bayes is founded on chance theory, and random forest (RF) employs a collection of decision trees. When precision farming practitioners make use of these various ways, researchers are able to make use of the benefits that each strategy offers, and researchers may tailor their selection to meet particular requirements and features of the farmed data that are available. Nischitha et al. developed a methodology utilizing machine-learning algorithms to determine appropriate crops for specific locations based on soil composition and climatic circumstances. Their methodology encompassed data acquisition from sources including management websites and weather datasets, data preprocessing to rectify and manage omitted values, and the use of machine-learning methods such as support vector machines and decision trees for predicting agricultural yields and rainfall. By entering factors such as humidity, temperature, and pH, the structure could discern trends in the data and offer recommendations for crop variety, including details on necessary seeds, market pricing, and estimated harvests for the suggested crops. The researchers validated the model by testing it with diverse datasets obtained from multiple farmers, encompassing lands with differing humidity, pH, and NPK values, thereby demonstrating its capacity to forecast yearly rainfall and suggest appropriate crops for the year 2020. Patil et al. aimed to assist Indian agriculturalists who typically cultivate similar crops and excessively utilize fertilizers with less variation. It has observed the ways in which technology, particularly machine learning, is benefitting many sectors and resolved to implement it in agriculture. A previous study predominantly employed machine learning with a singular variable; however, the authors intended to enhance their method by incorporating many variables. Their objective was to enhance crop yields while also identifying significant patterns for improved predictions. The method aims to counsel farmers on the optimal crops to plant in specific locales. Ultimately, the scientists developed an effective system for crop recommendation, discovering that the integration of specific machine-learning techniques, such as naïve Bayes and decision tree classifiers, yielded superior results compared to employing a singular method. This amalgamation enhanced the system's efficacy, rendering it beneficial for many crops and delivering precise recommendations for optimal planting and harvesting times. Elbasi et al. aimed to investigate how the application of smart technology and computer algorithms, such as those utilized in machine learning, could enhance agricultural practices for crop cultivation. Researchers examined various methods by which these technologies could assist in determining optimal times for planting, irrigating, and harvesting crops. Researchers discussed the challenges and benefits associated with the implementation of these technologies in agriculture. To demonstrate the efficacy of these technologies, trials were conducted, revealing that certain computer programs excelled at making predictions, such as recognizing the supreme appropriate crops for cultivation. The research indicates that the adoption of these technologies by farmers may enhance crop yield and reduce waste. Researchers evaluated numerous computer programs and identified one that demonstrated an accuracy of about 99.6%. The experts assert that the utilization of smart technology and computers can enhance agricultural practices and increase food production, particularly in times of scarcity. The researchers discovered that the integration of smart technologies and computer programs in agriculture is significant. Researchers evaluated several applications of these tools and demonstrated their potential profits for agriculturalists. Although the utilization of these technologies can be challenging, the outcomes thus far appear highly favorable. The research indicates that these technologies can assist farmers in increasing agricultural yields, minimizing waste, and ensuring food security for all. The researchers believe that further investigation in this domain can enhance agriculture and address certain challenges related to food security

4.2. Techniques for Unsupervised Learning

Crop prediction benefits greatly from unsupervised learning techniques, especially k-means clustering [23], which provide methods for deciphering intricate patterns in agricultural data. Unsupervised learning investigates the underlying patterns of the data without predetermined classifications, in contrast to supervised learning, which trains models on labelled datasets. One well-known method in this field is K-means clustering, which is notable for its capacity to divide datasets into discrete groups according to innate similarities. The use of k-means clustering in crop forecasts has the potential to reveal obscure patterns and trends in agricultural data, offering farmers and other stakeholders insightful information. The concepts and uses of k-means clustering in crop prediction are examined in this section. Suresh A. et al. proposed a forecasting technique for the primary crops grown in Tamil Nadu to address the rising need for agricultural output due to population expansion. Researchers employed the modified k-nearest neighbor (KNN) and k-means algorithms for classification and clustering, respectively. The goal was to forecast and comprehend the demand for production in order to optimize the crop yield. MATLAB R2020b and WEKA 3.8.6 were the tools used for classification and clustering. According to the findings, their suggested approach—which combined k-means and modified KNN—

performed better than conventional data-mining techniques. The study's authors came to the conclusion that modified KNN was the most successful algorithm among fuzzy, KNN, and modified KNN in predicting Tamil Nadu's key agricultural yields. To put it simply, the researchers used k-means in combination with modified KNN to create a crop yield prediction model, proving its superiority over conventional techniques and laying the groundwork for future research including more sophisticated algorithms. Naik and Venkatesh investigate the significance of elements like soil type, water, weather conditions, and plant nutritional content in determining crop production; the authors of the study addressed nutrition management in groundnut crops in India [38]. This study sought to identify shortages in both primary and micronutrients, in contrast to earlier studies that frequently only looked at the main nutrients. For their experiments, researchers used photos taken from crop fields using an ESP32 camera. The Visual Geometry Group (VGG16) [39] architecture was used to classify these pictures. The k-means clustering approach was used by the researchers to determine the percentages of nutrient deficiencies. The importance of primary and micronutrient deficiencies as a major cause of lower agricultural yields was emphasized in the conclusion. The suggested approach provides a workable answer to the difficulties farmers encounter in efficiently regulating crop nutrition by employing automatic detection and supplying deficient percentages. By more accurately and promptly treating nutrient deficiencies, this robotic method not only expedites the procedure but also reduces crop expenditure and ecological pollution. In order to increase the precision of crop yield forecasts, Suvitha, and Rathi created the proximity likelihood maximization data clustering (PLMDC) method, specifically for bare and highly scattered agricultural huge statistics [40]. The PLMDC methodology was a methodical procedure that began with a logical linear regression model to purge extraneous data. Following the use of a clustering technique centered on weight-based Manhattan distance and similarity, a genetic algorithm with a carefully thought-out fitness function was used to pick features. Notably, the authors improved the first clustering phase in their suggested PLMDC methodology by using the k-means clustering algorithm, a popular and successful clustering technique. K-means improved the PLMDC technique's overall precision by making it easier to organize data points into discrete clusters according to similarity. The outcomes showed that the PLMDC technique outperformed other methods in terms of assembling precision for both sparse and highly distributed data, obtaining better accuracy with less time and space complexity. The PLMDC technique was more efficient overall because it placed a strong importance on data preparation, planned clustering, and feature choice using genetic algorithms, containing the assimilation of k-means.

4.3. Techniques for Deep Learning

The usage of DL methods in crop prediction is examined in this section, with particular attention paid to their exceptional object detection capabilities [41,42]. A type of machine learning called deep learning (DL) has shown a notable capacity to classify and examine intricate patterns in statistics. Neural networks are used in crop forecast algorithms to identify and comprehend challenging elements in agricultural photography, including crop types, health problems, and development stages. Deep-learning techniques, which are well-known for their capacity to automatically build hierarchical representations, present encouraging developments in raising the accuracy and effectiveness of crop prediction models. Hani et al. performed a comparative investigation of semi-supervised and deep-learning-based methodologies for fruit identification and enumeration in apple orchards [43]. Their findings indicated that traditional methods, such as Gaussian mixture models, surpassed faster R-CNN, U-Net, CNN, and other deep-learning algorithms in output surveying. Koirala et al. showed the effectiveness of deep-learning techniques in identifying important structures in their analysis of the DL approach for fruit counting and yield estimate. For predicting the fruit load, the authors particularly suggested using deep regression, CNN detectors, and LSTM algorithms, emphasizing the adaptability of these methods in agricultural settings [44]. According to Van Klompenburg et al.'s comprehensive evaluation of the literature on machine-learning-based agricultural production prediction, neural networks—more especially, CNNs as well as LSTM, and deep neural networks—are widely employed in this domain [45]. The researchers emphasized that different research used different numbers of characteristics, and that some forecasts depend on item identification and counting instead of conventional tabular data. Researchers also noticed that feature selection techniques varied widely. Lee et al. developed a self-predictive crop yield platform utilizing deep-learning algorithms, emphasizing agricultural diseases. The research revealed that the CNN algorithm surpassed the R-CNN and YOLO algorithms in the crop disease identification module [46]. The study demonstrated the efficacy of utilizing the rectified linear unit (ReLU) activation function in artificial neural networks by highlighting its superior performance in the crop yield prediction (CYP) module. Turning their attention to the integration of DL approaches, Chlingaryan et al. investigated the field of applying ML techniques to estimate nitrogen status and predict crop production [47]. The results indicated that advances in machine learning, especially in the field of deep learning, are expected to provide affordable solutions. Zhang et al. conducted a thorough study of DL applications in dense agricultural settings, covering a variety of tasks in a survey that showed that DL is excellent at handling dense agricultural environments, including yield estimation, detection, counting, and recognition and classification [48].

4.4. Techniques for Ensemble Learning

The utilization of ensemble-learning approaches in crop forecasting is demonstrated in this section, along with their importance and effect on enhancing forecast accuracy. Several models are combined in ensemble learning to increase overall robustness and performance. This method combines various algorithms in the context of crop prediction, leveraging their combined power to generate predictions that are more accurate and dependable. In order to mitigate the shortcomings of separate models and create more robust and flexible crop prediction arrangements, ensemble approaches like bagging and boosting are crucial. The methods, benefits, and results of using ensemble-learning techniques in precision agriculture are surveyed in this section, which also clarifies how researchers affect crop prediction models. In order to report the intricate issue of accurate crop prediction in the aspect of weather variability, Agarwal et al. suggested a novel approach that makes use of ensemble learning [49]. Merging forecasts from many ML algorithms, acknowledging the intrinsic shortcomings of distinct models, and utilizing the combined advantages of several strategies, this methodology seeks to increase accuracy. Using five distinct machine-learning methods, the authors trained on a variety of datasets, choosing the best performers to build an ensemble model. By recognizing and taking into account the different strengths and shortcomings of distinct models, this strategic ensemble methodology aimed to strengthen the firmness and flexibility in crop recommendations. According to the study, ensemble learning is particularly effective at handling complicated cultivated data, offers a strong outline for assessment, and has the potential to increase crop recommendation systems' efficiency. The main objective was to encourage better farming methods and increased crop yields, which would benefit the country and farmers alike. The use of machine learning for crop yield prediction was examined by Keerthana et al., who concentrated on ensemble methods to increase accuracy [50]. Their study focused on using supervised and unsupervised learning techniques to forecast crop types based on location information. The authors highlighted the importance of climatic conditions by selecting 28,242 cases with seven essential characteristics after conducting a thorough search and analysis of the data from several sources. Notably, researchers tested decision tree algorithms and neural networks, determining the latter's efficacy. The conclusion emphasized the effective implementation of a crop yield prediction system, particularly noting the Ensemble of Decision Tree Regressor combined with AdaBoost Regressor as a powerful tool for enhancing accuracy. This approach addresses important agricultural issues by providing farmers with useful advice on crop selection based on location and weather. In keeping with the ambitious Agenda Zero Hunger by 2030, Isaac et al. looked into the use of tree-based ensemble-learning models for crop compatibility as well as production prediction [51]. The study's goals were to develop and assess ensemble-learning models based on predictive analytics trees and to comprehend the intricate relationships between crop performance and environmental factors. With an accuracy of 99.32%, the experimental findings showed remarkable model performance using a publicly available Kaggle dataset. Particularly noteworthy was the capacity of gradient-tree-based ensemble models, including LightGBM and XGBoost, to surpass conventional machine-learning models and show how researchers could change crop management tactics for increased yields. The findings of the study highlighted the important influence of variables like rainfall and potassium levels on crop selection in particular areas. The research's ramifications go beyond providing farmers with useful tools for decision-making, enabling them to allocate resources optimally, adjust irrigation schedules, and modify farming methods to suit the unique needs of various crops, all of which will lead to increased productivity. The discovery of critical elements affecting crop growth, such as rainfall, potassium, and phosphorus, brought attention to the significance of sustainable farming methods and promoted focused and effective fertilization techniques with favorable environmental effects.

5. Diverse Agricultural Techniques Employing Numerous Forecasting Models

Agriculture is an essential and intrinsic human activity, reflecting our fundamental relationship with the soil and our nourishment [52,53]. It involves the intentional and methodical growth of crops, the management of livestock, and the conservation of natural assets, primarily aimed at producing food, fiber, and several basic items vital for living [54]. This longstanding habit, intricately embedded in human history, spans millennia, illustrating our inherent need to utilize the land's resources for sustenance and health. The multifaceted area of agriculture involves the prudent management of agricultural resources, the strategic allotment of arable land, and the implementation of a wide range of agricultural practices refined over generations [55]. Farmers adeptly manipulate the environment using these strategies to promote crop development and livestock raising, acting as stewards of the land and its produce. Farming extends beyond its fundamental function of providing nourishment: it represents the lasting relationship between humans and the environment, encapsulating the complex interaction of convention, novelty, and the relentless drive to nourish, attire, and support our societies [56]. There are several categories of farming such as traditional farming, and modern farming, and several essential classifications of agriculture, distinguishing two principal classifications: conventional farming and modern farming, the latter of which includes precision farming. Conventional farming denotes customary agricultural practices that are historically entrenched and frequently dependent on human labor, and established procedures are discussed. In sharp contrast, modern farming, including precision farming, represents a paradigm change characterized by the integration of contemporary tools and data-driven methodologies. Modern farming includes precision farming, which uses cutting-edge technologies like IoT sensors, AI, and remote sensing to improve farming practices. This classification establishes a basis for comprehending the dynamic evolution of agriculture, encompassing both traditional techniques and cutting-edge technological advancements in farming.

5.1. Conventional Technique of Agriculture

Traditional farming, a venerable technique that has supported communities for generations, constitutes a fundamental aspect of world food supply. This ancient system is fundamentally based on a succession of labor-intensive operations that align with the seasonal cycles and the capriciousness of nature. Traditional agriculture fundamentally relies on meticulous field preparation, wherein the soil is laboriously cultivated to establish fertile conditions for crop cultivation. The selection of seeds is a critical decision, informed by years of agricultural knowledge that identifies seeds best adapted to native environment and soil circumstances. To ensure that every seed is placed in the soil at the proper depth and spacing, the planting or seeding process is carried out carefully, often by hand [57]. Traditional farming, as shown in Section 5.2 below, heavily depends on natural resources, especially seasonal rainfall, which serves as the primary irrigation source. Compost and animal dung are examples of natural fertilizers that farmers employ to improve soil fertility as part of their commitment to the land. Crop cultivation necessitates a two-pronged approach, as conventional farmers also have to deal with the persistent problem of unwanted plants, carefully removing weeds that threaten the health of their prized harvests [58]. The agricultural cycle culminates in the celebratory harvest, during which the products of labor are meticulously gathered using traditional implements such as sickles or scythes. The choice of crops for cultivation illustrates the deep relationship between traditional agriculture and local communities, as this decision is shaped by the market response, local tastes, and the suitability of crops to the area's particular requirements. The tenacity and wisdom of generations of farmers who have maintained the land to provide sustenance for their people are demonstrated by traditional agriculture. Figure 2 depicts the conventional agricultural methodology. The goal of conventional agriculture is to produce as much food as possible by using chemical pesticides, fertilizers, and high-yield crop varieties. It uses irrigation systems, mono-cropping, and mechanical farming methods, all of which contribute to increased productivity and efficiency. Conventional farming can cause soil erosion, water pollution, and a decline in biodiversity, even if it satisfies the ecosphere's expanding food demand. Its conservational impact is being reduced, nevertheless, by incorporating innovations in sustainable practices.

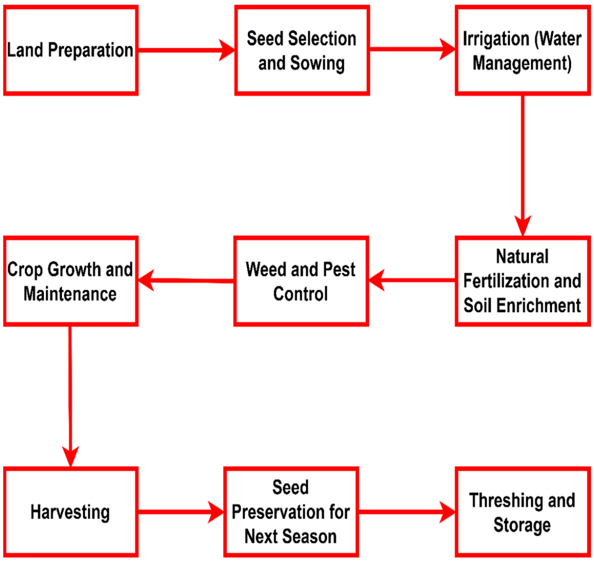

Figure 2. Conventional agricultural methodology.

5.2. Contemporary Precision Agriculture Technique

Precision farming is a transformative strategy in contemporary agriculture, utilizing breakthrough technologies to enhance agricultural methods. It exemplifies a data-driven methodology in agriculture, where every aspect of the growing process is meticulously controlled, from seed assortment to reserve organization and harvesting. The fundamental principle of precision agricultural is the accurate, site-specific comprehension of the agricultural land, enabling farmers to make informed decisions and take action accordingly. Using a number of modern technologies, such as GPS, IoT devices, remote sensing, and data analytics, this method makes it easier to monitor, analyze, and adjust in real time. Precision farming represents not merely a technological advancement but a profound revolution, offering enhanced yields, diminished resource waste, and sustainable agriculture, while addressing the trials of environmental sustainability and food security amid altering climatic conditions and a growing global population [59]. Figure 3 depicts the groundwork of precision agriculture. Figure 3 illustrates the essential components of the Precision Agriculture Foundation. Consider it akin to a toolkit for contemporary agriculture. This toolbox contains IoT gadgets that gather critical data from the farm. Subsequently, there exists AI, akin to an intelligent brain, that utilizes these data to make astute selections for the farm. Finally, we have robotics, which function as beneficial agricultural machinery. These technologies collaboratively assist agriculturalists in making knowledgeable decisions regarding crops and resources, so increasing the efficiency and productivity of agriculture. It resembles possessing an advanced technological assistant for agriculturalists. Like a smart farming recipe, Figure 4 shows the sequential steps in precision farming. Agriculture robotics, which are essentially high-tech farm, perform activities and transmit data to a cloud database, which functions similarly to a large, intelligent storage facility. After that, data analytics analyzes all of the farm’s data and makes astute decisions with the use of artificial intelligence, or a smart brain. Additionally, there are wired and wireless IOT (fancy farm) sensors in the fields that communicate data to the identical cloud database. Everything is connected by the cloud database, which functions as its heart. Lastly, the cloud database provides notifications and prompts to the end user services, which may include farmers or anybody else with an interest such as having a computerized farming helper—this clever technique makes farms more productive and efficient.

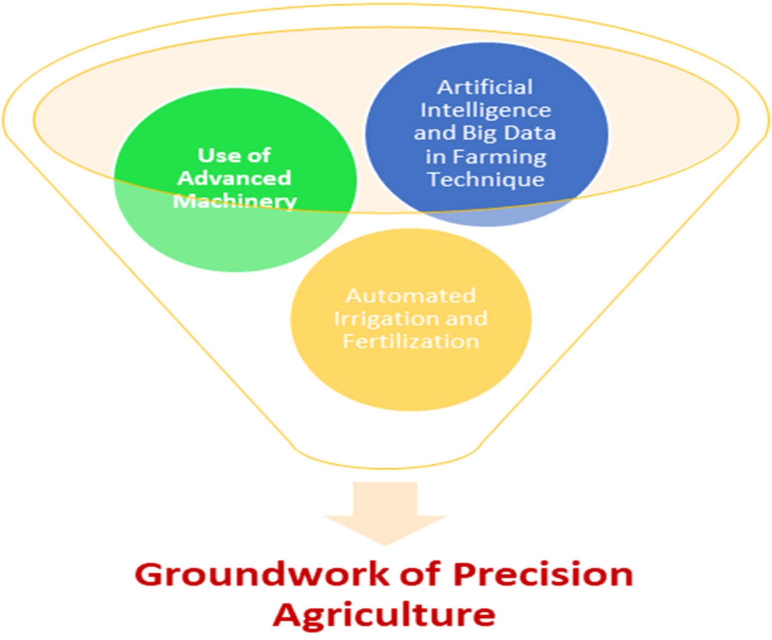

Figure 3. Groundwork of precision agriculture.

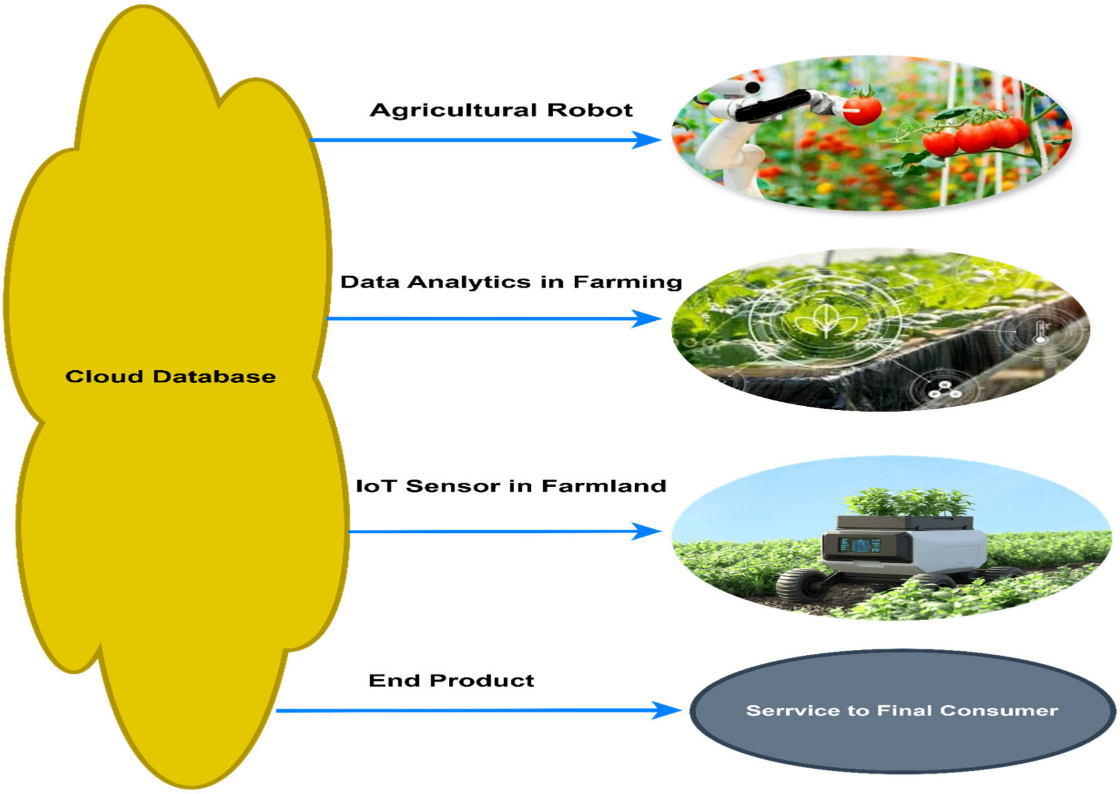

Figure 4. Procedure for efficient farming.

5.3. The Forecasting of Crops

Crop prediction, a critical area of agricultural science and technology, holds significant importance in the modern agricultural environment. It represents a refined interdisciplinary methodology that integrates data science, agronomy, and tools to predict crop yields, enhance assets distribution, and advance farm sustainability [59]. This systematic subject has grown in popularity in the reaction to the increasing worldwide demand for food, necessitating novel techniques to enhance agricultural output and address the difficulties posed by weather alteration and resource restriction. The foundation of crop prediction is the idea that farmers and other agricultural stakeholders may make well-informed decisions about the crop choice, planting schedules, and handling of resources with the help of insights based on data. This summary provides an overview of the methodologies, models, and technologies that support crop prediction, examining its numerous elements, applications, and consequences for sustainable and resilient agricultural systems [60].

Figure 5 demonstrates the sequential process by which artificial intelligence tools are integrated into precision farming. The process commences with the crop dataset, which encompasses vital farming information. The data undergoes data preprocessing, during which it is categorized into a training set and a test set to guarantee that the AI prototypes are provided with accurate information. The core building block of an AI-driven system is the AI models with which it interferes, which includes deep learning, machine learning, reinforcement learning, and ensemble learning, each of which has unique characteristics. In order to help farmers, maximize crop management, reduce waste, and increase yields, these models analyze the data and produce forecasts, making agriculture more intelligent and effective.

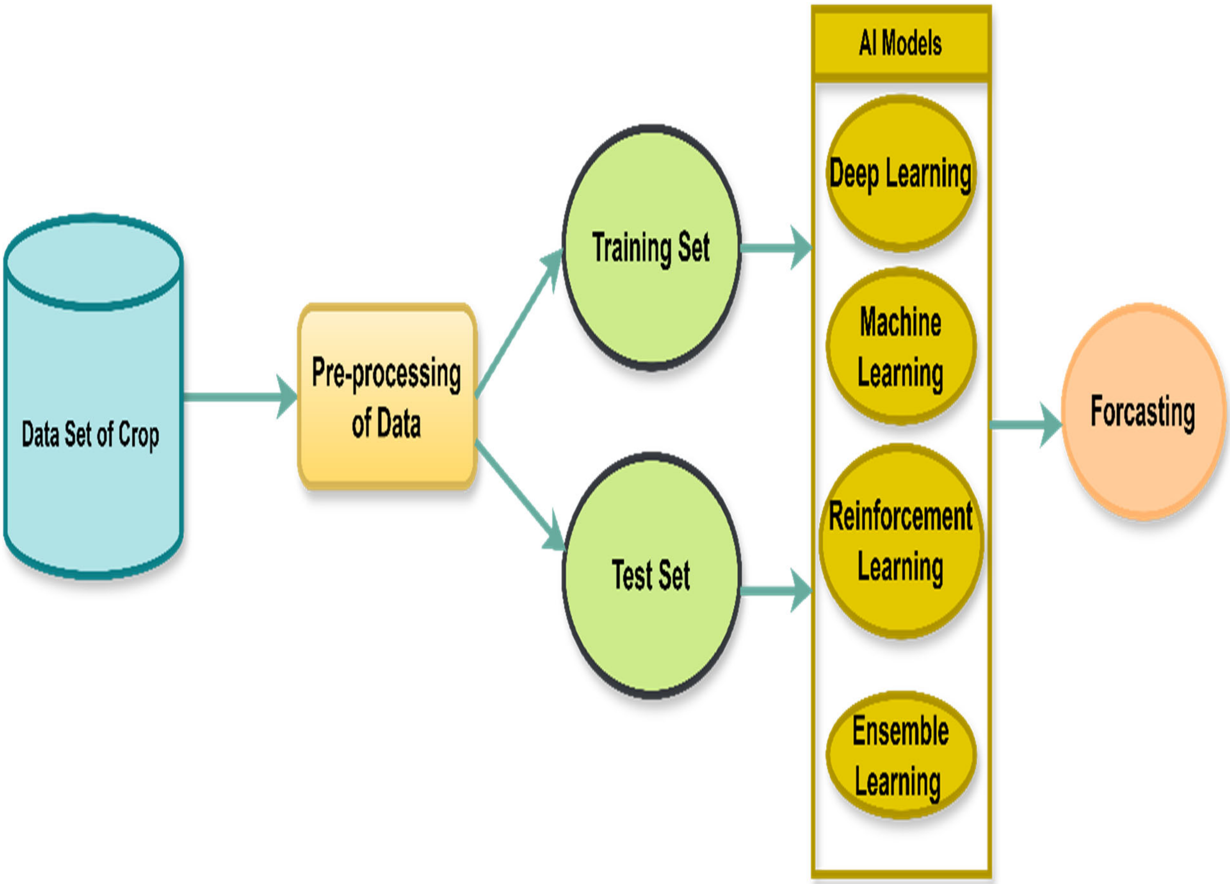

Figure 5. Application of artificial-intelligence-based techniques in agricultural precision.

5.4. Scope of Precision Agriculture in Crop Forecasting

Precision farming has gained appeal as a comprehensive agricultural management system in recent years due to its ability to provide accurate, regional approaches to crop oversight and choice-making. The utilization of IoT sensors in agricultural regions underpins the crop forecasting of precision farming [61]. In order to gather a variety of data points, such as crop health indicators, weather patterns, and soil moisture levels, these sensors are positioned throughout the agricultural landscape. Predictive modelling is based on this information. Crop forecasting benefits greatly from artificial intelligence's sophisticated data analytics skills [62]. Large datasets collected by IoT devices are analyzed using AI algorithms. Patterns, trends, and correlations that are not visible using traditional methods are found in the data. Predictive models powered by AI are designed to anticipate agricultural yields, identify pests or illnesses early on, and choose the best times to plant. Additionally, remote sensing technologies—such as drones and satellite imagery—that provide an aerial view of the fields make data collection easier. By offering pertinent data on crop health and growth, these technologies improve prediction accuracy [63].

5.5. Evaluation of Contemporary Models for Agricultural Yield Forecasting

The performance of several learning algorithm categories—deep learning, machine learning, ensemble learning, and reinforcement learning—is thoroughly compared in this portion of the paper. We assess these algorithms' effectiveness in light of the study's objectives. This performance research is crucial for assessing how well various teaching approaches fit into the designated agricultural environment. It helps identify the algorithms that are most effective in increasing crop productivity, reducing waste, and making planting, irrigation, and harvesting decisions easier. We concentrated exclusively on performance analyses of models generated within the current seven-year period (2019–2025).

Table 2, in detail, presents an outline of diverse methodologies in crop prediction utilizing precision agriculture, emphasizing the reference publications, algorithms used, and the associated performance indicators. Pawar et al. employed the naïve Bayes algorithm in supervised learning, attaining a Cohen's Kappa Score reflecting 95% accuracy [64]. Bondre and Mahagaonkar utilized SVMs with notable attainment, achieving an accuracy of 99.47% [65]. Mayagopal and Bhargavi executed the M5 Prime technique, achieving an accuracy rate of 85% [66], whereas Mupangwa et al. utilized both k-nearest neighbors (KNN), and linear regression, resulting in accuracies of 54% and 58%, respectively [67]. Pawar et al. employed the k-means algorithm within the framework of unsupervised learning, with an accuracy of 67.875% [64].

Table 2. Comparative examination of contemporary models employed for crop prediction and precision agriculture.

Techniques	Year	Authors	Algorithm(s)	Accuracy	Types of Vegetation
Supervised learning	(2021)	Pawar et al. [64]	NB	95%	Staple grains, pulses, oilseeds, vegetables, and fruits
	(2019)	Bondre and Mahagaonkar [65]	SVM	99.47%	Wheat, rice, pulses, oilseeds, maize, and vegetables
	(2019)	Mayagopal and Bhargavi [66]	M5 Prime	85%	Wheat rice, pulses, oilseeds, maize, and vegetables
	(2020)	Mupangwa et al. [67]	LR KNN	58% 54%	Maize
	(2022)	Murugamani et al. [68]	SVM	98.34%	Lettuce
	(2024)	Senapati et al. [69]	SVM	97.2%	Multiple vegetation types depend on input and regional suitability
Unsupervised learning	(2021)	Pawar et al. [64]	K-means	67.875%	Trees, shrubs, and grasses
Deep learning	(2020)	Muneshwara et al. [70]	ANN	98%	Multiple vegetation based on soil fertility and local agronomic conditions
	(2020)	Khaki et al. [71]	CNN	85.82%	Corn (maize) and soybean
	(2021)	Agarwal and Tarar [72]	RNN LSTM	97% 97%	Wheat, rice, pulses, oilseeds, maize, and vegetables
	(2020)	Kwaghtyo, Dekera Kenneth, and Christopher Ifeanyi Eke et al. [73]	ANN	98%	Pulses, wheat, oilseeds, maize, vegetables, fruits, and legumes
	(2023)	Saranya et al. [74]	CNN & GAN	96.58%	Rice, wheat, maize, pulses, oilseeds, vegetables, and fruits
	(2024)	Sharma & Vardhan [75]	Object Detection Algorithm YOLO	82.5%	Cotton, wheat, and corn
	(2024)	Yan et al. [76]	YOLOv8s	99.6%	Apple fruits, tree branches, and trunks
	(2025)	Thimmegowda [77]	ANN	95.26%	Cotton

Table 2. *Cont.*

Techniques	Year	Authors	Algorithm(s)	Accuracy	Types of Vegetation
Ensemble learning	(2021)	Suruliandi et al. [78]	Bagging	89%	Wheat, maize, rice, pulses, oilseeds, and vegetables
	(2020)	Mishra et al. [79]	Adaptive Enhancement	99.69%	Rice

Figure 6 depicts an evaluation of the accuracy of models from 2019 to 2024 examined in this study. This investigation examines the efficacy of these models, providing insights into their predictive powers and precision.

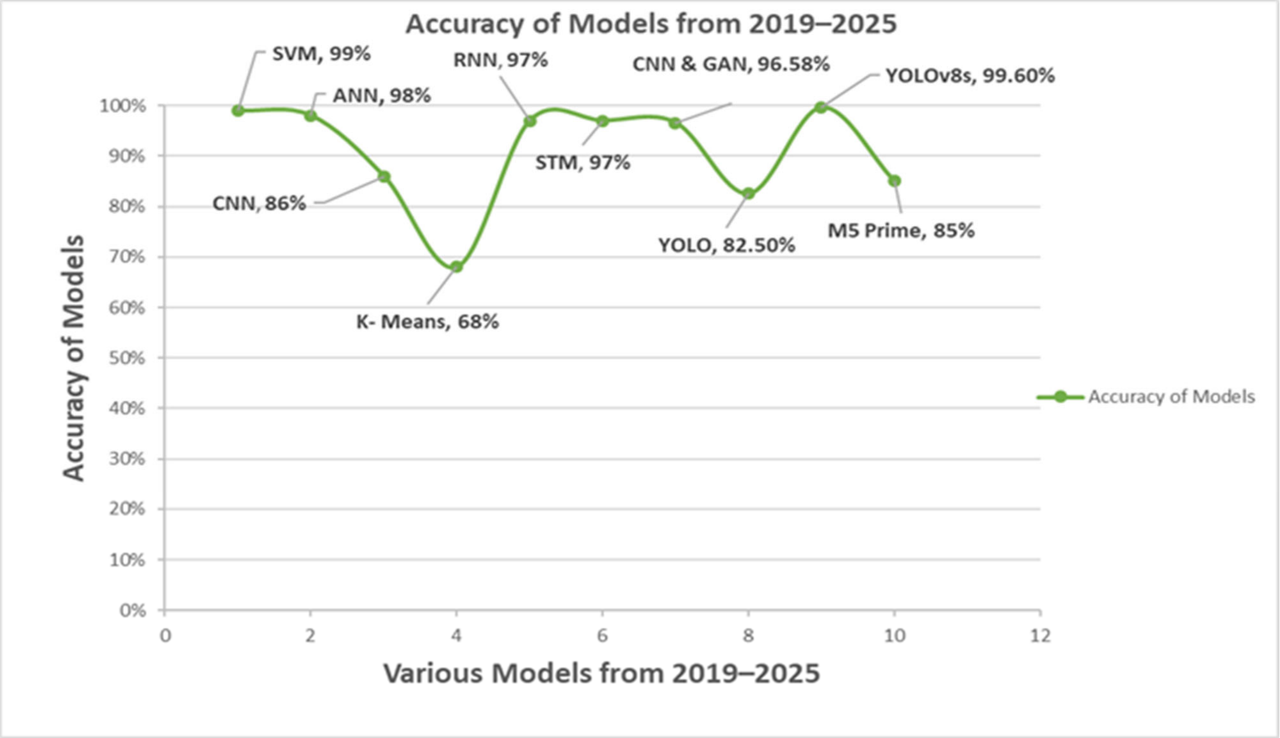

Figure 6. Accuracy of various models from 2019 to 2025.

Deep-learning methodologies demonstrated encouraging outcomes, with Muneshwara et al. achieving a 98% accuracy with artificial neural networks [70], Khaki et al. attaining an accuracy rate of 85.82% with convolutional neural networks [71], and Agarwal and Tarar [72,73] utilizing LSTM models and recurrent neural networks, mutually reaching a notable 97% accuracy. Suruliandi et al. investigated ensemble-learning strategies, namely, employing bagging, which achieved an accuracy rate of 89% [78]. Mishra et al. employed adaptive boosting, attaining an impressive accuracy of 99.69% with a 100% enhancement utilizing the R2 Score and mean absolute deviation (MAD) [79]. This comprehensive assessment provided significant insights into the various methodologies and their associated performance results in precision agriculture for crop forecasting [80]. In order to increase the performance rate of robotic harvesting and provide technical assistance for the development of intelligent apple-gathering robots, Yan et al. proposed an analysis and segmentation technique for the classification of apple fruits, subdivisions, and trunks [76].

6. Challenges and Future Scope of Agriculture Forecasting

This section illustrates the challenges associated with employing precision agriculture for forecasting crop yields [81,82]. These challenges encompass ensuring data accuracy, obtaining appropriate technology, and adhering to rules [83,84]. Comprehending and conveying these difficulties are critical for the effective implementation of precision farming in farming, as seen in following subsection. In precision agriculture, a significant issue is safeguarding the confidentiality and security of farm data. The researchers investigated a variety of different technical approaches to make sustainability feasible [85]. Utilizing numerous intelligent sensors and specialized technology to monitor the farm enables us to gather a substantial amount of critical data [86]. These data provide visions into the soil and the performance of the crops, and forecast the expected yield [87,88]. However, we must ensure that this information does not get into the inappropriate hands. Concerns exist with hackers and unauthorized individuals accessing this farm information [89,90]. To address this, we must develop robust security protocols to safeguard the data and adhere to regulations regarding information protection [91,92]. This approach ensures the confidentiality of farmers' information and prevents the unauthorized dissemination of agricultural data [93]. It is a significant difficulty; yet, using robust security measures and adhering to regulations facilitate its resolution [94,95]. Acquiring the appropriate quantity of accurate information from many sources poses a challenge in precision agriculture [96]. We utilize intelligent sensors, specialized technology, and historical records to obtain this information. However, at times, the data we receive may be flawed. It may be erroneous or lacking. This may lead to inaccuracies in our forecasts regarding the farm. Additionally, we require substantial data to ensure the accuracy of our projections. However, for minor farms or locations with limited data, this can be challenging. It is akin to needing numerous jigsaw pieces to perceive the complete image. Acquiring sufficient and accurate data poses a difficulty, particularly for smaller farms or locations with few records available. In specific areas, the utilization of new technology and reliable Internet is challenging due to its limited availability [97]. This complicates the ability of farmers to utilize and gain advantages from precision agricultural techniques. For these solutions to be effective, robust technology and high-speed Internet are required in order to connect smart sensors and facilitate data sharing [98]. However, in many regions, the absence of these resources hinders farmers from employing modern agricultural techniques that could benefit them [99]. It resembles possessing an impressive tool without all the requisite components for optimal functionality. Figure 7 depicts the challenges in agricultural precision.

The restricted availability of advanced technology and high-speed Internet in certain areas poses a barrier, since it hinders the implementation of precision farming, hence diminishing its efficacy for such farmers. Adhering to the regulations and standards established by local and national authorities on data utilization, land management, and environmental stewardship poses challenges for precision farming practitioners. The numerous regulations can complicate and increase the costs of precision farming. It resembles possessing numerous disparate puzzle pieces that must align perfectly. Adhering to regulations on data utilization, land stewardship, and environmental conservation is a significant problem for farmers employing precision agriculture. It introduces additional layers of complexity and may incur higher costs to adhere to all regulations accurately. A challenge in farming is ensuring that precision farming techniques are applicable to all types of farms, whether tiny family-owned or large commercial enterprises. Occasionally, solutions suitable for large farms are incompatible with smaller, more diverse agricultural operations. It resembles possessing a tool that functions effectively in a large garden but is ill-suited for a small one with diverse flora. Implementing precision farming across diverse farm sizes and types is a difficulty, as a universal solution is inadequate for agriculture. A solution is required that can accommodate various farm configurations and dimensions.

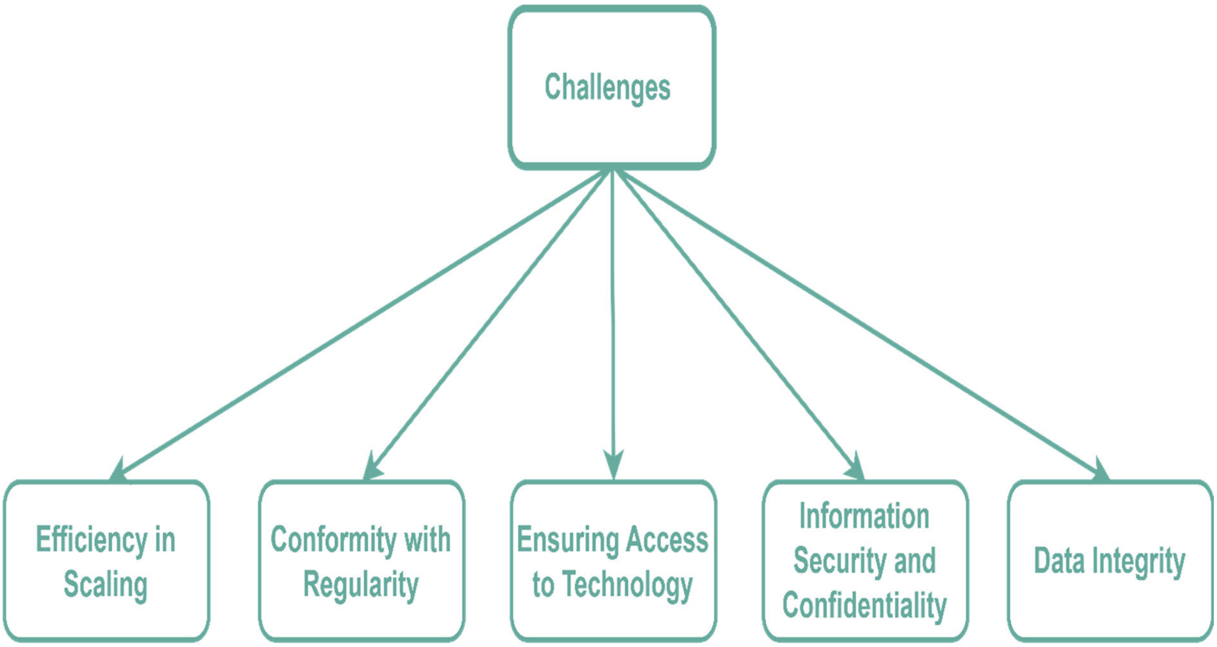

Figure 7. Challenges in agricultural precision.

Future Scope of Agriculture Forecasting

This section anticipates the future trajectory of precision farming, as illustrated in Figure 8 This entails investigating innovative opportunities such as employing drones, adjusting to climate change, and enhancing agricultural sustainability. These prospective trajectories seek to enhance agriculture by making it more intelligent, efficient, and sustainable for our planet and food resources. Advancing the broader utilization of agricultural robots represents a substantial advancement in the modernization of diverse farming practices. These autonomous devices are designed to perform a range of functions, including harvesting, planting, and pest management. Their incorporation into agricultural methods has the potential to enhance sustainability and efficiency in the future. Agricultural robots can minimize the reliance on manual labor by assuming labor-intensive and time-consuming tasks, hence lowering working costs and enhancing precision in farming practices. This shift concerning robotics enhances resource efficiency and guarantees the precise management and cultivation of crops, providing an extra dynamic and environmentally sustainable option for forthcoming farming. Promoting worldwide collaboration and the unrestricted sharing of data in precision farming is a crucial development in the evolution of agriculture. This collaborative strategy seeks to create a thorough and accurate knowledge library that can equip farming decision-makers with extensive data. By fostering worldwide collaboration, agricultural investors can jointly acquire data from various areas, climates, and farming methodologies, resulting in a more comprehensive understanding of crop management and resource distribution. This global knowledge amalgamation is a crucial asset for refining precision farming techniques, optimizing predictive prototypes, and executing ecological practices on a larger level, thereby advancing the worldwide quest for food security and environmentally sustainable agriculture. Modifying precision farming methods for urban and vertical agriculture yields substantial advantages by optimizing resource utilization and minimizing environmental impact. In these constrained environments, utilizing data-driven methodologies facilitates efficient resource allocation, conserves water, and reduces the total environmental impact. This strategy corresponds with the growing demand for nearby-sourced, new goods while guaranteeing ecological methods. One great way to meet the demand for locally grown, ecologically friendly produce is to adapt accurate farming methods for metropolitan and vertical agriculture.

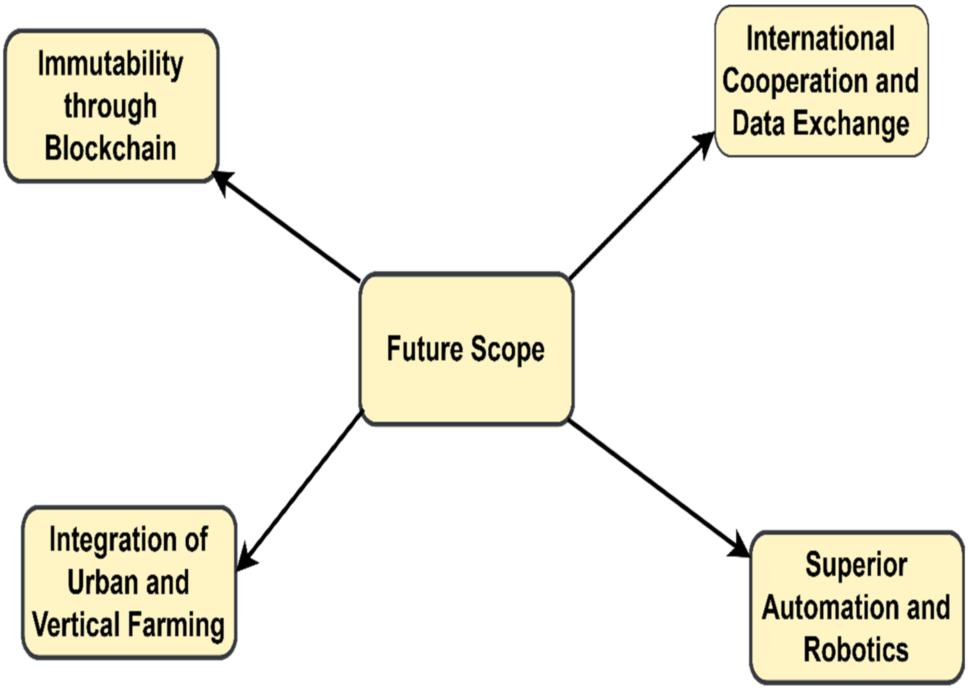

Figure 8. Perspectives for the future in precision agriculture.

Figure 8 depicts the perspectives for the future in precision agriculture. Blockchain technology is a disruptive force, paving the way for an age of reliance, liability, and openness in the agriculture supply chain. The implementation of blockchain technology for the comprehensive traceability of agricultural products represents an innovative method that enhances transparency and trust in the supply chain. Utilizing blockchain technology, each phase of a product's trajectory, from production to consumption, is documented and steadily preserved. This provides a trustworthy method of verifying the provenance of the product while also allowing customers to track the origins and path of their food. It ensures that claims about sustainable, fair-trade, or organic practices can be independently verified, which increases consumer confidence. Furthermore, it has great potential for food safety since it can quickly pinpoint the source of contamination during a recall, safeguarding public health and enhancing the integrity of the entire food industry.

Despite major developments in precision agriculture, certain technologies necessitate further investigation in order to fully harness their potential. The amalgamation of artificial intelligence and machine learning with real-time field data is yet still developing, enabling further research to create adaptable models capable of providing precise, site-specific recommendations. Furthermore, enhancements in remote sensing technologies, such hyperspectral imaging and drone-based monitoring, require refinement for an improved resolution, cost-effectiveness, and user-friendliness. The advancement of affordable, resilient sensor networks capable of continuous, multi-parameter monitoring in varied situations is another vital field requiring increased focus. Moreover, blockchain technology for facilitating transparent and secure data-sharing among stakeholders presents interesting applications, although it remains inadequately investigated in agricultural contexts. Collectively, these nascent technologies signify crucial frontiers for enhancing the efficacy and accessibility of precision agriculture. Notwithstanding its advancements, precision agriculture continues to confront numerous pressing issues that require resolution. Data privacy and security continue to be significant issues, as farmers increasingly depend on digital platforms to handle sensitive information. There is an urgent need to provide cost-effective technology that may be utilized by small and medium-sized farms, rather than solely by huge enterprises. Moreover, issues about the interoperability of various systems and equipment impede the smooth incorporation of new technologies. Environmental sustainability is a crucial concern, as precision techniques must guarantee enduring soil health and resource conservation while optimizing yield. For precision agriculture to be widely and responsibly implemented, these problems must be resolved.

Deep-learning and machine-learning models are crucial for accurate crop prediction by examining extensive and intricate information, including meteorological patterns, soil conditions, and historical yield data, to reveal concealed patterns and correlations. These models may analyze present statistics from sensors and satellite imagery to generate precise, timely forecasts regarding crop growth, yield, and possible threats such as disease outbreaks or drought stress. Deep-learning models, specifically, excel at processing high-dimensional data and can progressively enhance their predictions as additional data are acquired. These tools facilitate improved planning, resource management, and risk mitigation in agriculture by delivering accurate forecasts to farmers. Deep-learning and machine-learning models can be customized for small-scale farms and regions with minimal digitization by emphasizing simplified, cost-effective solutions. Lightweight models necessitating low processing resources can be implemented on basic cellphones or offline devices, hence diminishing the requirement for costly infrastructure. Transfer-learning techniques can adjust pre-trained models to local situations with minimal data. Moreover, creating intuitive mobile applications with straightforward interfaces might enable farmers to effortlessly obtain predictive insights without requiring sophisticated technological expertise. Collaborations with local organizations can facilitate training and maintenance, guaranteeing that these technologies remain accessible and sustainable in resource-constrained settings.

7. Conclusions

The current state of agricultural forecasting with precision farming methods has been thoroughly examined in this paper. This objective has brought to light the complexities and potential of this ever-changing field. Precision farming, which combines cutting-edge technologies, promotes cooperation, and advocates for international data interchange, has the capacity to significantly renovate the farming industry and promote improved sustainability, efficiency, and transparency. Our capacity to provide insightful information on the different obstacles and forthcoming ways of precision farming, as well as our analytical evaluation of existing models, highlight our contribution to this discussion as the study's researchers. Our work demonstrates the evolutionary potential of precision agriculture and its crucial role in shaping the future of agriculture by balancing scientific novelty with environmental accountability, thereby supporting an agricultural sector that is more productive, flexible, and data-informed. The prior investigation indicates a robust performance, attaining an overall prediction accuracy ranging from a mean value of 90% to 99.69% nearly across different crop varieties, contingent upon the input attributes and data quality. The quantitative indicators, including the R^2 score and mean absolute error (MAE), from the prior investigation validated the model's capacity to accurately align the anticipated yields with the actual results, with R^2 values consistently being around 90%. The model demonstrated robustness by sustaining a high accuracy when evaluated with incomplete or noisy data, signifying its effective generalization to real-world scenarios. Its versatility across many crops and locales underscores its practical significance, while several limitations were observed, including minor performance declines in places characterized by extremely fluctuating meteorological conditions or insufficient historical statistics.

Author Contributions: Conceptualization, data curation, formal analysis, investigation, methodology, resources, software, validation, writing—original draft, and writing—review and editing, K.S.; conceptualization, data curation, formal analysis, investigation, methodology, resources, software, validation, writing—original draft, and writing—review and editing, M.Y.; formal analysis, investigation, resources, and visualization, D.B.; methodology, software, validation, formal analysis, and investigation, S.B.; conceptualization, supervision, data curation, formal analysis, investigation, methodology, resources, and software, F.M. All authors have read and agreed to the published version of the manuscript.

Funding: This work is funded by national funds through FCT—Fundação para a Ciência e a Tecnologia, I.P., under the support of UID/05105: REMIT—Investigação em Economia, Gestão e Tecnologias da Informação.

Data Availability Statement: The authors affirm that no dataset or code was created for this study.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Mukhamedova, K.R.; Cherepkova, N.P.; Korotkov, A.V.; Dagasheva, Z.B.; Tvaronavičienė, M. Digitalisation of agricultural production for precision farming: A case study. *Sustainability* **2022**, *14*, 14802. [CrossRef]
2. Botero-Valencia, J.; García-Pineda, V.; Valencia-Arias, A.; Valencia, J.; Reyes-Vera, E.; Mejia-Herrera, M.; Hernández-García, R. Machine Learning in Sustainable Agriculture: Systematic Review and Research Perspectives. *Agriculture* **2025**, *15*, 377. [CrossRef]
3. Nyéki, A.; Neményi, M. Crop yield prediction in precision agriculture. *Agronomy* **2022**, *12*, 2460. [CrossRef]
4. Malashin, I.; Tynchenko, V.; Gantimurov, A.; Nelyub, V.; Borodulin, A.; Tynchenko, Y. Predicting sustainable crop yields: Deep learning and explainable AI tools. *Sustainability* **2024**, *16*, 9437. [CrossRef]
5. Sishodia, R.P.; Ray, R.L.; Singh, S.K. Applications of remote sensing in precision agriculture: A review. *Remote Sens.* **2020**, *12*, 3136. [CrossRef]
6. Mouratiadou, I.; Lemke, N.; Chen, C.; Wartenberg, A.; Bloch, R.; Donat, M.; Gaiser, T.; Basavegowda, D.H.; Helming, K.; Yekani, S.A.H.; et al. The Digital Agricultural Knowledge and Information System (DAKIS): Employing digitalisation to encourage diversified and multifunctional agricultural systems. *Environ. Sci. Ecotechnol.* **2023**, *16*, 100274. [CrossRef]
7. Braidotti, G.; De Nobili, M.; Piani, L. Integrated Use of Local and Technical Soil Quality Indicators and Participatory Techniques to Select Them. A Review of Bibliography and Analysis of Research Strategies and Outcomes. *Sustainability* **2020**, *13*, 87. [CrossRef]
8. Al-Gaadi, K.A.; Hassaballa, A.A.; Tola, E.; Kayad, A.G.; Madugundu, R.; Alblewi, B.; Assiri, F. Prediction of potato crop yield using precision agriculture techniques. *PLoS ONE* **2016**, *11*, e0162219. [CrossRef]
9. Thilakarathne, N.N.; Bakar, M.S.A.; Abas, P.E.; Yassin, H. A cloud enabled crop recommendation platform for machine learning-driven precision farming. *Sensors* **2022**, *22*, 6299. [CrossRef]
10. Yasam, S.; Nair, S.A.H.; Kumar, K.S. Supervised learning-based seed germination ability prediction for precision farming. *Soft Comput.* **2022**, *26*, 13133–13144. [CrossRef]
11. Shaikh, T.A.; Mir, W.A.; Rasool, T.; Sofi, S. Machine learning for smart agriculture and precision farming: Towards making the fields talk. *Arch. Comput. Methods Eng.* **2022**, *29*, 4557–4597. [CrossRef]
12. Finger, R.; Swinton, S.M.; El Benni, N.; Walter, A. Precision farming at the nexus of agricultural production and the environment. *Annu. Rev. Resour. Econ.* **2019**, *11*, 313–335. [CrossRef]
13. Tsouros, D.C.; Bibi, S.; Sarigiannidis, P.G. A review on UAV-based applications for precision agriculture. *Information* **2019**, *10*, 349. [CrossRef]
14. Ahmed, N.; De, D.; Hussain, I. Internet of Things (IoT) for smart precision agriculture and farming in rural areas. *IEEE Internet Things J.* **2018**, *5*, 4890–4899. [CrossRef]
15. Yue, S.; Li, P.; Hao, P. SVM classification: Its contents and challenges. *Appl. Math.-J. Chin. Univ.* **2003**, *18*, 332–342. [CrossRef]
16. Dreiseitl, S.; Ohno-Machado, L. Logistic regression and artificial neural network classification models: A methodology review. *J. Biomed. Inform.* **2002**, *35*, 352–359. [CrossRef] [PubMed]
17. Guo, G.; Wang, H.; Bell, D.; Bi, Y.; Greer, K. KNN model-based approach in classification. In *On the Move to Meaningful Internet Systems 2003: CoopIS, DOA, and ODBASE: OTM Confederated International Conferences CoopIS, DOA, and ODBASE 2003 Catania, Sicily, Italy, November 3–7, 2003 Proceedings*; Springer: Berlin/Heidelberg, Germany, 2003; pp. 986–996. [CrossRef]

18. Yang, F.J. An implementation of naive bayes classifier. In Proceedings of the 2018 International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, USA, 12–14 December 2018; pp. 301–306. [CrossRef]
19. Parmar, A.; Katariya, R.; Patel, V. A review on random forest: An ensemble classifier. In *International Conference on Intelligent Data Communication Technologies and Internet of Things (ICICI) 2018, Coimbatore, India, 7–8 August 2018*; Springer International Publishing: Cham, Switzerland, 2019; pp. 758–763. [CrossRef]
20. Nischitha, K.; Vishwakarma, D.; Ashwini, M.N.; Manjuraju, M.R. Crop prediction using machine learning approaches. *Int. J. Eng. Res. Technol. (IJERT)* **2020**, *9*, 23–26. [CrossRef]
21. Patil, P.; Panpatil, V.; Kokate, S. Crop prediction system using machine learning algorithms. *Int. Res. J. Eng. Technol. (IRJET)* **2020**, *7*, 748–753.
22. Elbasi, E.; Zaki, C.; Topcu, A.E.; Abdelbaki, W.; Zreikat, A.I.; Cina, E.; Shdefat, A.; Saker, L. Crop prediction model using machine learning algorithms. *Appl. Sci.* **2023**, *13*, 9288. [CrossRef]
23. Thakre, L.; Nikhar, M. Crop Prediction Techniques with K-Means Algorithms. In *Optimization Methods for Engineering Problems*; Apple Academic Press: New York, NY, USA, 2023; pp. 225–237. Available online: https://www.taylorfrancis.com/chapters/edit/10.1201/9781003300731-16/crop-prediction-techniques-means-algorithms-laxman-thakre-mayur-nikhar (accessed on 3 April 2023).
24. Suresh, A.; Kumar, P.G.; Ramalatha, M. Prediction of major crop yields of Tamilnadu using K-means and Modified KNN. In Proceedings of the 2018 3rd International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 15–16 October 2018; pp. 88–93. [CrossRef]
25. Ariza-Sentís, M.; Vélez, S.; Martínez-Peña, R.; Baja, H.; Valente, J. Object detection and tracking in Precision Farming: A systematic review. *Comput. Electron. Agric.* **2024**, *219*, 108757. [CrossRef]
26. Nilsback, M.E.; Zisserman, A. A visual vocabulary for flower classification. In Proceedings of the 2006 IEEE Computer Society Conference on Computer Vision and Pattern recognition (CVPR'06), New York, NY, USA, 17–22 June 2006; Volume 2, pp. 1447–1454. [CrossRef]
27. Hou, S.; Feng, Y.; Wang, Z. Vegfru: A domain-specific dataset for fine-grained visual categorization. In Proceedings of the IEEE International Conference on Computer Vision, Venice, Italy, 22–29 October 2017; pp. 541–549.
28. Van Horn, G.; Mac Aodha, O.; Song, Y.; Cui, Y.; Sun, C.; Shepard, A.; Adam, H.; Perona, P.; Belongie, S. The inaturalist species classification and detection dataset. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 18–23 June 2018; pp. 8769–8778.
29. Wu, X.; Zhan, C.; Lai, Y.K.; Cheng, M.M.; Yang, J. Ip102: A large-scale benchmark dataset for insect pest recognition. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Long Beach, CA, USA, 15–20 June 2019; pp. 8787–8796.
30. Gené-Mola, J.; Sanz-Cortiella, R.; Rosell-Polo, J.R.; Morros, J.R.; Ruiz-Hidalgo, J.; Vilaplana, V.; Gregorio, E. Fuji-SfM dataset: A collection of annotated images and point clouds for Fuji apple detection and location using structure-from-motion photogrammetry. *Data Brief* **2020**, *30*, 105591. [CrossRef]
31. Wang, R.; Liu, L.; Xie, C.; Yang, P.; Li, R.; Zhou, M. Agripest: A large-scale domain-specific benchmark dataset for practical agricultural pest detection in the wild. *Sensors* **2021**, *21*, 1601. [CrossRef] [PubMed]
32. de Jong, S.; Baja, H.; Tamminga, K.; Valente, J. Apple mots: Detection, segmentation and tracking of homogeneous objects using mots. *IEEE Robot. Autom. Lett.* **2022**, *7*, 11418–11425. [CrossRef]
33. Mignoni, M.E.; Honorato, A.; Kunst, R.; Righi, R.; Massuquetti, A. Soybean images dataset for caterpillar and Diabrotica speciosa pest detection and classification. *Data Brief* **2022**, *40*, 107756. [CrossRef] [PubMed]
34. Amraoui, K.E.; Lghoul, M.; Ezzaki, A.; Masmoudi, L.; Hadri, M.; Elbelrhiti, H.; Simo, A.A. Avo-AirDB: An avocado UAV Database for agricultural image segmentation and classification. *Data Brief* **2022**, *45*, 108738. [CrossRef]
35. Giakoumoglou, N.; Pechlivani, E.M.; Sakelliou, A.; Klaridopoulos, C.; Frangakis, N.; Tzovaras, D. Deep learning-based multi-spectral identification of grey mould. *Smart Agric. Technol.* **2023**, *4*, 100174. [CrossRef]
36. Ariza-Sentís, M.; Vélez, S.; Valente, J. Dataset on UAV RGB videos acquired over a vineyard including bunch labels for object detection and tracking. *Data Brief* **2023**, *46*, 108848. [CrossRef] [PubMed]
37. Güldenring, R.; Van Evert, F.K.; Nalpantidis, L. RumexWeeds: A grassland dataset for agricultural robotics. *J. Field Robot.* **2023**, *40*, 1639–1656. [CrossRef]
38. Venkatesh, K.; Naik, K.J. An IoT framework for groundnut crop yield prediction using K-means algorithm. In Proceedings of the 2021 International Conference on Data Analytics for Business and Industry (ICDABI), Sakheer, Bahrain, 25–26 October 2021; pp. 266–271. [CrossRef]
39. Islam, M.M.; Adil, M.A.A.; Talukder, M.A.; Ahamed, M.K.U.; Uddin, M.A.; Hasan, M.K.; Sharmin, S.; Rahman, M.; Debnath, S.K. DeepCrop: Deep learning-based crop disease prediction with web application. *J. Agric. Food Res.* **2023**, *14*, 100764. [CrossRef]
40. Vani, P.S.; Rathi, S. Improved data clustering methods and integrated A-FP algorithm for crop yield prediction. *Distrib. Parallel Databases* **2023**, *41*, 117–131. [CrossRef]

41. Mustapha, A.A.; Yoosuf, M.S. Exploring the efficacy and comparative analysis of one-stage object detectors for computer vision: A review. *Multimed. Tools Appl.* **2024**, *83*, 59143–59168. [CrossRef]
42. Balakrishna, S.; Mustapha, A.A. Progress in multi-object detection models: A comprehensive survey. *Multimed. Tools Appl.* **2023**, *82*, 22405–22439. [CrossRef]
43. Häni, N.; Roy, P.; Isler, V. A comparative study of fruit detection and counting methods for yield mapping in apple orchards. *J. Field Robot.* **2020**, *37*, 263–282. [CrossRef]
44. Koirala, A.; Walsh, K.B.; Wang, Z.; McCarthy, C. Deep learning–Method overview and review of use for fruit detection and yield estimation. *Comput. Electron. Agric.* **2019**, *162*, 219–234. [CrossRef]
45. Van Klompenburg, T.; Kassahun, A.; Catal, C. Crop yield prediction using machine learning: A systematic literature review. *Comput. Electron. Agric.* **2020**, *177*, 105709. [CrossRef]
46. Lee, S.; Jeong, Y.; Son, S.; Lee, B. A self-predictable crop yield platform (SCYP) based on crop diseases using deep learning. *Sustainability* **2019**, *11*, 3637. [CrossRef]
47. Chlingaryan, A.; Sukkarieh, S.; Whelan, B. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Comput. Electron. Agric.* **2018**, *151*, 61–69. [CrossRef]
48. Zhang, Q.; Liu, Y.; Gong, C.; Chen, Y.; Yu, H. Applications of deep learning for dense scenes analysis in agriculture: A review. *Sensors* **2020**, *20*, 1520. [CrossRef]
49. Agarwal, B.; Pokhriyal, S.; Vats, S.; Sharma, V.; Rawat, P.; Bajaj, M. Crop prediction using ensemble learning. In Proceedings of the 2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 3–5 August 2023; pp. 90–95. [CrossRef]
50. Keerthana, M.; Meghana, K.J.M.; Pravallika, S.; Kavitha, M. An ensemble algorithm for crop yield prediction. In Proceedings of the 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), Tirunelveli, India, 4–6 February 2021; pp. 963–970. [CrossRef]
51. Nti, I.K.; Zaman, A.; Nyarko-Boateng, O.; Adekoya, A.F.; Keyeremeh, F. A predictive analytics model for crop suitability and productivity with tree-based ensemble learning. *Decis. Anal. J.* **2023**, *8*, 100311. [CrossRef]
52. Zheng, Y.Y.; Kong, J.L.; Jin, X.B.; Wang, X.Y.; Su, T.L.; Zuo, M. CropDeep: The crop vision dataset for deep-learning-based classification and detection in precision agriculture. *Sensors* **2019**, *19*, 1058. [CrossRef]
53. Santos, T.T.; De Souza, L.L.; dos Santos, A.A.; Avila, S. Grape detection, segmentation, and tracking using deep neural networks and three-dimensional association. *Comput. Electron. Agric.* **2020**, *170*, 105247. [CrossRef]
54. Sudars, K.; Jasko, J.; Namatevs, I.; Ozola, L.; Badaukis, N. Dataset of annotated food crops and weed images for robotic computer vision control. *Data Brief* **2020**, *31*, 105833. [CrossRef]
55. Häni, N.; Roy, P.; Isler, V. MinneApple: A benchmark dataset for apple detection and segmentation. *IEEE Robot. Autom. Lett.* **2020**, *5*, 852–858. [CrossRef]
56. Garcia-Llorente, M.; Rubio-Olivar, R.; Gutierrez-Briceno, I. Farming for life quality and sustainability: A literature review of green care research trends in Europe. *Int. J. Environ. Res. Public Health* **2018**, *15*, 1282. [CrossRef] [PubMed]
57. Pawlak, K.; Kołodziejczak, M. The role of agriculture in ensuring food security in developing countries: Considerations in the context of the problem of sustainable food production. *Sustainability* **2020**, *12*, 5488. [CrossRef]
58. Morell-Hart, S.; Dussol, L.; Fedick, S.L. Agriculture in the ancient Maya lowlands (Part 1): Paleoethnobotanical residues and new perspectives on plant management. *J. Archaeol. Res.* **2023**, *31*, 561–615. [CrossRef]
59. Ghosh, S.; Dasgupta, R. Machine learning and precision farming. In *Machine Learning in Biological Sciences: Updates and Future Prospects*; Springer Nature Singapore: Singapore, 2022; pp. 239–249. [CrossRef]
60. Avadhani, S.S.; Arun, A.B.; Govinda, V.; Inamdar, J.S.I. Crop Prediction Models—A Review. In *Emerging Technologies in Data Mining and Information Security: Proceedings of IEMIS 2018*; Springer: Singapore, 2019; Volume 755, pp. 13–17. [CrossRef]
61. Maduranga, M.W.P.; Abeysekera, R. Machine learning applications in IoT based agriculture and smart farming: A review. *Int. J. Eng. Appl. Sci. Technol.* **2020**, *4*, 24–27. [CrossRef]
62. Benos, L.; Tagarakis, A.C.; Dolias, G.; Berruto, R.; Kateris, D.; Bochtis, D. Machine learning in agriculture: A comprehensive updated review. *Sensors* **2021**, *21*, 3758. [CrossRef] [PubMed]
63. Yang, D.; Zhao, J.; Lan, Y.; Wen, Y.; Pan, F.; Cao, D.; Hu, C.; Guo, J. Research on farmland crop classification based on UAV multispectral remote sensing images. *Int. J. Precis. Agric. Aviat.* **2021**, *4*, 29–35. [CrossRef]
64. Pawar, S.; Dere, S.; Akangire, A.; Kamble, H.; Shrawne, S. Smart farming using machine learning. *Smart Comput.* **2021**, 73–81. Available online: https://www.researchgate.net/publication/351692492_SMART_FARMING_USING_MACHINE_LEARNING (accessed on 3 April 2023).
65. Bondre, D.A.; Mahagaonkar, S. Prediction of crop yield and fertilizer recommendation using machine learning algorithms. *Int. J. Eng. Appl. Sci. Technol.* **2019**, *4*, 371–376. [CrossRef]
66. Maya Gopal, P.S.; Bhargavi, R. Selection of important features for optimizing crop yield prediction. *Int. J. Agric. Environ. Inf. Syst. (IJAEIS)* **2019**, *10*, 54–71. [CrossRef]

67. Mupangwa, W.; Chipindu, L.; Nyagumbo, I.; Mkuhlani, S.; Sisito, G. Evaluating machine learning algorithms for predicting maize yield under conservation agriculture in Eastern and Southern Africa. *SN Appl. Sci.* **2020**, *2*, 952. [CrossRef]
68. Murugamani, C.; Shitharth, S.; Hemalatha, S.; Kshirsagar, P.R.; Riyazuddin, K.; Naveed, Q.N.; Islam, S.; Ali, S.P.M.; Batu, A. Machine Learning Technique for Precision Agriculture Applications in 5G-Based Internet of Things. *Wirel. Commun. Mob. Comput.* **2022**, *2022*, 6534238. [CrossRef]
69. Senapati, C.; Senapati, S.; Swain, S.; Patra, K.J.; Pattanayak, B.K.; Laha, S.R. Advancements in Precision Agriculture: A Machine Learning-Based Approach for Crop Management Optimization. In *Sustainable Farming Through Machine Learning*; CRC Press: Boca Raton, FL, USA, 2024; pp. 162–173.
70. Muneshwara, M.S.; Gracias, A.A.; Neha, C.G.; Preethi, A.S. Soil fertility analysis and crop prediction using machine learning. *Int. J. Innov. Technol. Explor. Eng.* **2020**, *9*, 380–383. [CrossRef]
71. Khaki, S.; Wang, L.; Archontoulis, S.V. A CNN-RNN framework for crop yield prediction. *Front. Plant Sci.* **2020**, *10*, 1750. [CrossRef]
72. Agarwal, S.; Tarar, S. A hybrid approach for crop yield prediction using machine learning and deep learning algorithms. *J. Phys. Conf. Ser.* **2021**, *1714*, 012012. [CrossRef]
73. Kwaghtyo, D.K.; Eke, C.I. Smart farming prediction models for precision agriculture: A comprehensive survey. *Artif. Intell. Rev.* **2023**, *56*, 5729–5772. [CrossRef]
74. Saranya, T.; Deisy, C.; Sridevi, S.; Anbananthen, K.S.M. A Comparative study of deep learning and Internet of Things for precision agriculture. *Eng. Appl. Artif. Intell.* **2023**, *122*, 106034. [CrossRef]
75. Sharma, S.; Vardhan, M. Advancing precision agriculture: Enhanced weed detection using the optimized YOLOv8T model. *Arab. J. Sci. Eng.* **2024**, 1–18. [CrossRef]
76. Yan, B.; Liu, Y.; Yan, W. A novel fusion perception algorithm of tree branch/trunk and apple for harvesting robot based on improved YOLOv8s. *Agronomy* **2024**, *14*, 1895. [CrossRef]
77. Thimmegowda, M.N.; Manjunatha, M.H.; Lingaraj, H.; Soumya, D.V.; Jayaramaiah, R.; Sathisha, G.S.; Nagesha, L. Comparative analysis of machine learning and statistical models for cotton yield prediction in major growing districts of Karnataka, India. *J. Cotton Res.* **2025**, *8*, 6. [CrossRef]
78. Suruliandi, A.; Mariammal, G.; Raja, S.P. Crop prediction based on soil and environmental characteristics using feature selection techniques. *Math. Comput. Model. Dyn. Syst.* **2021**, *27*, 117–140. [CrossRef]
79. Mishra, S.; Mishra, D.; Santra, G.H. Adaptive boosting of weak regressors for forecasting of crop production considering climatic variability: An empirical assessment. *J. King Saud Univ.-Comput. Inf. Sci.* **2020**, *32*, 949–964. [CrossRef]
80. Gupta, M.; Abdelsalam, M.; Khorsandroo, S.; Mittal, S. Security and privacy in smart farming: Challenges and opportunities. *IEEE Access* **2020**, *8*, 34564–34584. [CrossRef]
81. Belanche, A.; Martín-García, A.I.; Fernández-Álvarez, J.; Pleguezuelos, J.; Mantecón, Á.R.; Yáñez-Ruiz, D.R. Optimizing management of dairy goat farms through individual animal data interpretation: A case study of smart farming in Spain. *Agric. Syst.* **2019**, *173*, 27–38. [CrossRef]
82. Guesmi, B.; Serra, T. Can we improve farm performance? The determinants of farm technical and environmental efficiency. *Appl. Econ. Perspect. Policy* **2015**, *37*, 692–717. [CrossRef]
83. Dholu, M.; Ghodinde, K.A. Internet of things (IoT) for precision agriculture application. In Proceedings of the 2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 11–12 May 2018; pp. 339–342. [CrossRef]
84. Stewart-Koster, B.; Anh, N.D.; Burford, M.A.; Condon, J.; Van Qui, N.; Van Bay, D.; Sammut, J. Expert based model building to quantify risk factors in a combined aquaculture-agriculture system. *Agric. Syst.* **2017**, *157*, 230–240. [CrossRef]
85. Rosen, M.A. Engineering sustainability: A technical approach to sustainability. *Sustainability* **2012**, *4*, 2270–2292. [CrossRef]
86. Donati, L.; Iotti, E.; Mordonini, G.; Prati, A. Fashion product classification through deep learning and computer vision. *Appl. Sci.* **2019**, *9*, 1385. [CrossRef]
87. Bendre, M.R.; Thool, R.C.; Thool, V.R. Big data in precision agriculture: Weather forecasting for future farming. In Proceedings of the 2015 1st International Conference on Next Generation Computing Technologies (NGCT), Dehradun, India, 4–5 September 2015; pp. 744–750. [CrossRef]
88. Aslan, M.F.; Sabanci, K.; Aslan, B. Artificial intelligence techniques in crop yield estimation based on Sentinel-2 data: A comprehensive survey. *Sustainability* **2024**, *16*, 8277. [CrossRef]
89. Singh, K.; Yadav, M.; Singh, Y.; Barak, D.; Saini, A.; Moreira, F. Reliability on the Internet of Things with designing approach for exploratory analysis. *Front. Comput. Sci.* **2024**, *6*, 1382347. [CrossRef]
90. Lu, J.; Li, J.; Fu, H.; Tang, X.; Liu, Z.; Chen, H.; Sun, Y.; Ning, X. Deep learning for multi-source data-driven crop yield prediction in northeast China. *Agriculture* **2024**, *14*, 794. [CrossRef]
91. Darwin, B.; Dharmaraj, P.; Prince, S.; Popescu, D.E.; Hemanth, D.J. Recognition of bloom/yield in crop images using deep learning models for smart agriculture: A review. *Agronomy* **2021**, *11*, 646. [CrossRef]

92. Pena, A.; Tejada, J.C.; Gonzalez-Ruiz, J.D.; Gongora, M. Deep learning to improve the sustainability of agricultural crops affected by phytosanitary events: A financial-risk approach. *Sustainability* **2022**, *14*, 6668. [CrossRef]
93. Teixeira, I.; Morais, R.; Sousa, J.J.; Cunha, A. Deep learning models for the classification of crops in aerial imagery: A review. *Agriculture* **2023**, *13*, 965. [CrossRef]
94. Joshi, A.; Pradhan, B.; Gite, S.; Chakraborty, S. Remote-sensing data and deep-learning techniques in crop mapping and yield prediction: A systematic review. *Remote Sens.* **2023**, *15*, 2014. [CrossRef]
95. Abbasi, M.; Váz, P.; Silva, J.; Martins, P. Machine learning approaches for predicting maize biomass yield: Leveraging feature engineering and comprehensive data integration. *Sustainability* **2025**, *17*, 256. [CrossRef]
96. Radočaj, D.; Jurišić, M. GIS-based cropland suitability prediction using machine learning: A novel approach to sustainable agricultural production. *Agronomy* **2022**, *12*, 2210. [CrossRef]
97. Assous, H.F.; AL-Najjar, H.; Al-Rousan, N.; AL-Najjar, D. Developing a sustainable machine learning model to predict crop yield in the Gulf countries. *Sustainability* **2023**, *15*, 9392. [CrossRef]
98. Ali, Z.; Muhammad, A.; Lee, N.; Waqar, M.; Lee, S.W. Artificial Intelligence for Sustainable Agriculture: A Comprehensive Review of AI-Driven Technologies in Crop Production. *Sustainability* **2025**, *17*, 2281. [CrossRef]
99. Tamayo-Vera, D.; Wang, X.; Mesbah, M. A review of machine learning techniques in agroclimatic studies. *Agriculture* **2024**, *14*, 481. [CrossRef]