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Advanced Machine Learning Architectures for Precision Crop Prediction: A Technical Evaluation of Model Performance, Challenges, and Future Directions

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Abstract

Innovations driven by technology and data-driven methodologies, precision farming has emerged as a revolutionary area in modern agriculture. This study presents a review of recent advancements in Machine Learning (ML) techniques employed for Crop Prediction, followed by performance analysis of recent models (2019-2023). It explores the integration of advanced technologies, collaborative aims, and data-centric approaches aimed at overcoming the challenges in traditional agriculture. This paper presents the capabilities and complexity of precision farming through an analysis of various ML, Deep Learning, Reinforcement Learning, and Ensemble Learning models. Emphasising the important role of global collaboration and data-sharing initiatives provides information on the precision farming industry's changing environment and shows future developments in the field.

Keywords:*Crop Prediction; Precision Agriculture; Deep Learning;Smart Farming;Machine Learning;*

1. Introduction

Crop prediction through precision farming is an academically captivating and advanced approach, that aligns with the evolving agricultural domain [1]. This method relies on the careful application of advanced technology, including remote sensing, to estimate crop yields. Its rapid ascent in the agricultural domain is reshaping farming practices, providing farmers with a data-centric strategy that significantly boosts overall productivity [2]. At the core of precision farming lies the use of satellite imagery, a powerful tool for generating dynamic vegetation index maps. These maps serve as invaluable guides for making well-informed decisions in agricultural practices. The process starts by classifying these maps into distinct zones, each corresponding to the health status of the vegetation. This spatial categorization enables strategic resource placement and agricultural practices.

A subsequent step involves carefully collecting crop yield samples within these zones, intricately correlated with adjacent vegetation indices. The development of sophisticated yield prediction algorithms plays a key role in generating precise forecasts, marking a departure from traditional agricultural methods. What distinguishes crop prediction through precision farming is its various impacts. Primarily, it redefines crop management by offering a real-time, data-driven approach, optimizing resource allocation, minimizing wastage, and ultimately leading to higher crop yields. Empowered with data-driven information, farmers can make timely decisions, enhancing agricultural efficiency and profitability [3].Furthermore, integrating ML and data analysis techniques broadens the horizons of crop prediction. These algorithms efficiently process large datasets and adapt to evolving conditions, continually improving prediction accuracy. Machine learning, in this context, emerges as a powerful tool for synthesizing multi-dimensional data sources, including soil quality assessments, weather data, and satellite imagery [4].

The inclusion of remote sensing, and ML in precision farming and crop prediction propels research and innovation. Scholars in this field actively explore avenues to improve predictive capabilities, develop user-friendly interfaces, and increase accessibility for farmers [5]. Crop prediction through precision farming stands as aninteresting domain of academic exploration and innovation, showcasing the transformative potential of modern technologies in agriculture. This fusion of technology and agriculture takes a forefront position in scientific research, poised to reshape the future of farming practices, promising increased efficiency, reduced waste, and higher crop yields [6].

Contributions:

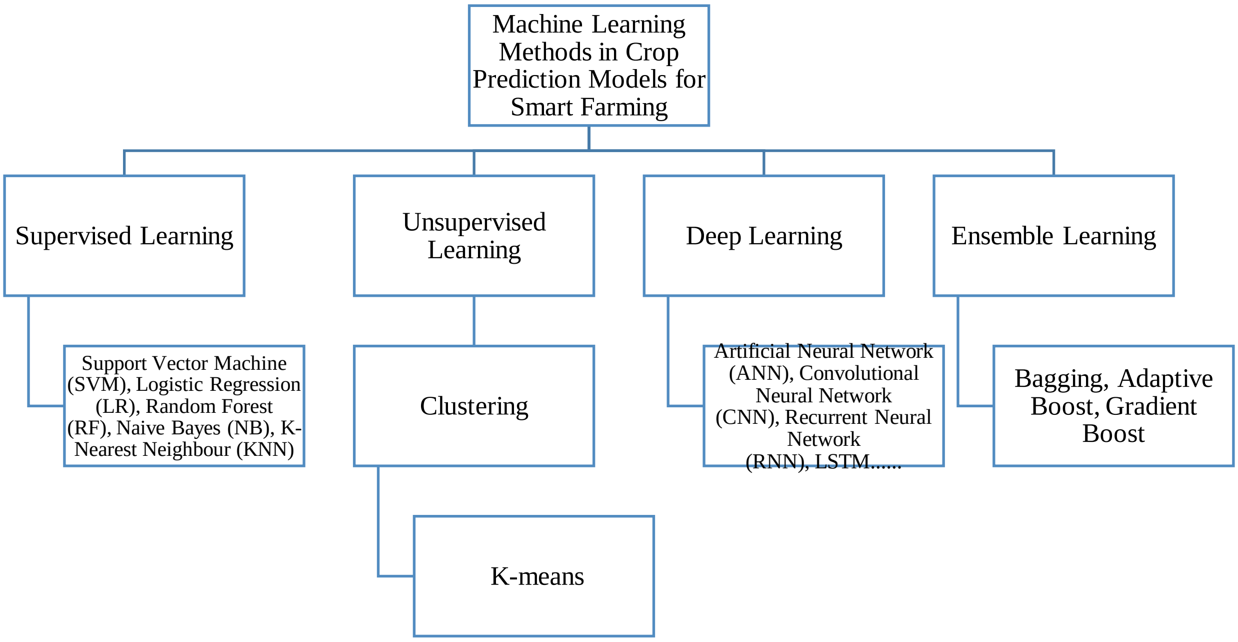
- A comprehensive study of ML Techniques,performance analysis, challenges, and future directions.
- Performed performance comparison of recent machine learning, deep learning, reinforcement learning, and ensemble learning models in the context of crop prediction.
- Identification and discussion of the challenges and obstacles faced in crop prediction through precision farming techniques.
- Exploration of potential future directions, offering knowledge and a roadmap for further research, innovation, and development in precision farming and agriculture.

2 Literature Survey of ML Techniques in Precision Farming for Crop Prediction

In the context of our research, we have undertaken a comprehensive exploration of a curated selection of articles that explores deeply into the complex domain of crop prediction and precision farming techniques. Through a detailed analysis of these articles, we aim to uncover the latest trends, address pertinent challenges, and identify promising opportunities within crop prediction and precision farming. This exploration serves as a vital foundation for our research, enriching our understanding of the contemporary agricultural landscape and providing valuable knowledgeabout the innovative practices that are shaping the future of farming.

Pudumalar, S.et al [7], In their comprehensive study, the authors provide an advanced precision agriculture crop recommendation system, strategically using data mining techniques to offer precise crop recommendations aligned with the unique soil conditions of Indian farmers. The paper presentsan important role of crop selection in the domain of precision farming. A comprehensive literature survey follows, exploring the related studies and classification algorithms, laying a robust foundation for their research. The methodology elucidates the origins of their dataset, encompassing soil-specific attributes and using a sophisticated ensemble model. The result showcases the model's impressive performance in classifying liver disease data, regrettably, it does not explore the model's efficiency in the context of crop yield prediction. Khalid et al. [8], explored the application of precision agriculture techniques for predicting potato crop yield in three irrigated fields within Saudi Arabia. Employing GIS and remote sensing methods, the study used Landsat-8 and Sentinel-2 satellite imagery to estimate the tuber crop yield. The authors generated vegetation index maps using vegetation indices which were then divided into zones according to vegetation health evaluations. Next, stratified random sample locations were established, and crop yield samples were collected and correlated with adjacent vegetation indices, leading to the development of yield prediction algorithms. The study's findings indicated that these precision agriculture techniques were effective in predicting potato crop yield, with prediction errors ranging from 7.9 to 13.5% for Landsat-8 images and 3.8 to 10.2% for Sentinel-2 images. The authors highlighted the potential for these techniques to change agriculture by enhancing crop management and resource efficiency. However, the study's limited scope, focusing on just three irrigated fields in Saudi Arabia, suggests that the results may not be universally applied to other parts of the world or crops.Thilakarathne et al [9]built a recommendation method which is a cloud-enabled crop tool for ML-driven precision farming, which significantly advanced the field of precision farming. This innovative platform uses satellite imaging, soil sensors, weather stations, and other data sources that may all be analysed using machine-learning techniques to deliver tailored crop recommendations for individual farms. The authors comprehensively explore precision farming's potential, addressing the challenges of traditional farming methods and underscoring machine learning's advantages in crop prediction, such as efficient data processing. The authors detail the platform's design, encompassing data loading, preprocessing, model building, and generalization stages, along with its real-time capabilities and user-friendly interface. They emphasize the need for making these technologies accessible to farmers, particularly in remote areas, and highlight the importance of continued research and development to improve crop prediction accuracy and efficiency through machine learning.

Yasam et al [10] presented a supervised learning-based model to predict seed germination ability, a vital aspect of precision farming. They begin by emphasizing the significance of seed germination highlighting the drawbacks of conventional measurement methods, and propose a machine-learning approach as an alternative solution. They detail the materials and methods employed, showcasing the dataset of seed images and corresponding germination rates, data preprocessing, and presenting the model architecture, incorporating a CNN for feature extraction and a multilayer perceptron for classification. Hyperparameters and performance evaluation metrics are also expounded. The results indicate the model's superiority over traditional techniques and include insightful ablation studies. Shaikh, Tawseef Ayoub et al [11] explored Information and Communication Technology (ICT) and its transformative potential within traditional agriculture. They systematically explore a spectrum of advanced technologies, encompassing robotics, IoT devices, ML, and artificial intelligence, exploring their applicability in precision farming. The authors scrutinize the hurdles inherent to the integration of these technologies, including the formidable cost of equipment and the requisite expertise for proficient operation. Furthermore, a review of existing literature is presented, highlighting the utility of ML and AI in agriculture, particularly in domains such as crop yield prediction, disease detection, and soil analysis. Theyextend to the adoption of drones for crop surveillance and management, offering knowledgeof the advantages and complexities associated with their implementation. Finger, Robert et al [12] presented an extensive analysis of precision farming and its effects on the environment and agricultural output. They examined the most recent advancements in big data and technology to make it more precise, linked, efficient, and broadly applicable. They also addressed how PF technologies may be made more widely accessible and, thus, have a greater overall positive impact on society through advancements in the legal and technological infrastructure. They provided a thorough analysis of PF's present situation as well as its potential to change agriculture and advance sustainable development. They gave insights into the mechanisms, use, trends, and prospects of PF. Additionally, they looked at the policy elements of PF and how they related to other environmental and agricultural policies. Provided case studies and examples of successful PF implementation in different regions of the world, which can serve as a guide for farmers and policymakers.Tsouros, Dimosthenis C. et al [13], examined UAV-based applications in precision agriculture, exploring the transformative potential of emerging technologies like IoT and UAVs for real-time decision-making in agriculture. The review encompassed an analysis of hyperspectral imagery and associated techniques, evaluating the suitability of various sensors for different applications. Additionally, a survey addressed the utilization of DL in handling data. The authors highlighted the absence of a literature review specifically focusing on commonly employed techniques for utilizing and processing UAV imagery in agricultural contexts, emphasizing its essential role.



They emphasized the critical need for a standardized workflow, as the lack thereof hinders the widespread adoption of UAV systems in commercial precision agriculture applications. The diversity in procedures and methods among researchers pursuing the same goal may lead to suboptimal outcomes.

Ahmed et al [14], To monitor and manage agricultural and remote farms, this study presents a scalable network architecture that makes use of fog computing and a long-distance WiFi-based network inside the Internet of Things (IoT). To reduce network latency, the suggested approach provides a cross-layer-based

channel access and routing mechanism for sensing and actuating. The authors used testbed tests and simulations

to analyse the system's performance. The simulation study was conducted in two stages: first, the performance of the proposed Wireless Sensor Network (WSN) and WiLD network was evaluated individually. Next, the performance of the entire framework was evaluated by using the findings from the first phase. In the testbed evaluation, the authors detailed the evaluation processes and analyzed the architecture's performance.

Figure 1. ML Algorithms in Precision farming for Crop Prediction

Figure 1 illustrates various Machine Learning algorithms employed in precision farming for crop prediction. These include supervised learning techniques as well as deep learning methods such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). Ensemble methods like Gradient Boosting and Adaptive Boosting are also shown.

2.1 Supervised Learning Techniques

The implementation of Supervised Learning methods is widely recognized in precision farming. These methods encompass several well-established techniques, each contributing uniquely to the domain. SVM [15], LR [16], KNN [17], Naïve Bayes [18] and Random Forest [19] are among the most prevalent and extensively applied Supervised Learning methods. SVM excels in creating decision boundaries, LR is adept at modelling probabilities, KNN relies on proximity for classification, Naïve Bayes is based on probability theory, and RF utilizes an ensemble of decision trees. The utilization of these diverse methods allows precision farming practitioners to use the strengths of each approach, designing their choice based on specific requirements and characteristics of the agricultural data present.

Nischitha K.et al[20] proposed an approach that employs ML algorithms to identify suitable crops for certain sites depending on soil composition and weather conditions. Their approach involved data collection from sources like government websites and climate data, data preprocessing to clean and handle missing values, and the application of ML algorithms such as SVM and decision trees for crop and rainfall prediction. By inputting parameters like temperature, humidity, and pH, the system could identify patterns in the data and provide recommendations for crop selection, along with information on required seeds, market prices, and approximate yields for the recommended crops. Through testing the system with various datasets collected from different farmers, including lands with varying pH, humidity, and NPK values, the authors demonstrated the system's capability to predict annual rainfall and recommend suitable crops for the year 2020.Pavan Patil et al. [21] wanted to help Indian farmers who usually plant the same crops and use a lot of fertilizers without much change. They saw how technology, specifically ML, is helping in different areas and decided to use it for farming. While past research mostly used ML with just one factor, the authors planned to make their system better by using more factors. Their goal was to not only increase crop yields but also to find important patterns for better predictions. The purpose of the system is to advise farmers on which crops are best to cultivate in particular regions. In the end, the authors successfully created a helpful system for suggesting crops, and they found that combining certain ML methods, like naïve Bayes and decision tree classifiers, worked better than using just one. This combination improved the system's performance, making it useful for different crops and providing accurate suggestions for when to plant and harvest.

Ersin Elbasi et al. [22], wanted to see how using smart technology and computer programs, like those used in self-learning, could help farmers do a better job in growing crops. They looked at different ways these technologies could be helpful, like deciding when to plant, water, and harvest crops. They also talked about the difficulties and good things about using these technologies in farming. To show how well these technologies work, they did experiments and found that some computer programs were good at predicting things, like what kind of crops would grow best. The study suggests that if farmers use these technologies, they could grow more crops and waste less. They tried out many different computer programs and found one that worked well, almost 99.6% accurate. The researchers believe that using smart technology and computers can make farming better and help produce more food for everyone, especially when there's not enough. The researchers found that using smart technology and computer programs in farming is a big deal. They tested out different ways of using these technologies and showed that they could be very helpful for farmers. Even though it's not always easy to use these technologies, the results so far look really good. The study suggests that these technologies can help farmers grow more crops, waste less, and make sure there's enough food for everyone. The researchers think that more research in this area can make farming even better and help solve some of the problems we have with food.

2.2 Unsupervised Learning Techniques

Unsupervised learning techniques, particularly K-means clustering [23], are powerful in crop prediction, offering approaches to understanding complex patterns within agricultural data. Unlike supervised learning, where models are trained on labelled datasets, unsupervised learning explores the inherent structures of the data without predefined classifications. Within this domain, K-means clustering, a prominent technique, stands out for its ability to partition datasets into distinct groups based on inherent similarities. In crop prediction, the application of K-means clustering holds promise for uncovering hidden patterns and trends in agricultural data, providing valuable insights for farmers and stakeholders. This section explores the principles and applications of K-means clustering in crop prediction.

To meet the growing need for agricultural output brought on by population expansion, Suresh A. et al [24] proposed a forecasting approach for the key crops grown in Tamilnadu. For clustering and classification, they used the K-means and Modified K Nearest Neighbour (KNN) algorithms, respectively. The objective was to maximize crop yield by predicting and understanding the demand for production. The tools employed for clustering and classification were Matlab and WEKA. The results indicated that their proposed method, incorporating K-means and Modified KNN, outperformed traditional data mining approaches. The authors concluded that the study successfully predicted major crop yields in Tamilnadu, with Modified KNN emerging as the most effective algorithm among fuzzy, KNN, and Modified KNN. In essence, the authors applied K-means in conjunction with Modified KNN to develop a predictive model for crop yields, demonstrating its superiority over traditional methods and setting the stage for further exploration of advanced algorithms in future studies.Venkatesh and Naik[25] The authors conducted a study addressing nutrition management in groundnut crops in India, recognizing the importance of factors like soil type, water, environmental conditions, and plant nutritional content in determining crop yield. Unlike previous research that often focused solely on primary nutrients, this work aimed to detect both primary and micronutrient deficiencies. They employed ESP32 camera images captured from crop fields for experimentation. The classification of these images was carried out using the Visual Geometry Group (VGG16) [26] architecture. To estimate nutrient deficiency percentages, the authors implemented the K-Means clustering algorithm. The conclusion highlighted the significance of nutrient deficiency, both primary and micro, as a key factor contributing to reduced crop yields. The proposed method, utilizing automatic detection and providing deficiency percentages, offers a practical solution to the challenges faced by farmers in managing crop nutrition effectively. This automated approach not only streamlines the process but also helps minimize crop investments and environmental pollution by addressing nutrient deficiencies in a more precise and timely manner.

Vani, P. Suvitha, and S. Rathi [27] developed a Proximity Likelihood Maximisation Data Clustering (PLMDC) approach, particularly for both sparse and highly distributed agricultural big data to improve crop yield forecast accuracy. The PLMDC technique involved a systematic process that commenced with the cleansing of unnecessary data through a logical linear regression model. Subsequently, a clustering method based on similarity and weight-based Manhattan distance was applied, and feature selection was carried out using a genetic algorithm with a well-designed fitness function. Notably, the authors integrated the K-means clustering algorithm, a widely used and effective clustering technique, into their proposed PLMDC methodology to improve the initial clustering step. K-means facilitated the grouping of data points into distinct clusters based on similarity, thereby contributing to the overall precision of the PLMDC technique. The results demonstrated the superiority of the PLMDC technique in terms of clustering accuracy for both sparse and densely distributed data, achieving improved accuracy with minimal time and space complexity compared to existing methods. The emphasis on data preprocessing, strategic clustering, and feature selection through genetic algorithms, including the integration of K-means, contributed to the overall efficiency of the PLMDC technique.

2.3 Deep Learning Techniques

This section explores the application of DL techniques in crop prediction, focusing on their remarkable ability in object detection [28] [29]. DL is a subset of ML that has demonstrated a significant abilityto recognize and analyse complex patterns within data. In crop prediction, these techniques use neural networks to detect and understand the difficult features within agricultural imagery, such as crop types, health conditions, and growth stages. The utilization of deep learning methods, known for their ability to automatically learn hierarchical representations, offers promising advancements in improving the precision and efficiency of crop prediction models.

A comparison study of DL-based techniques and semi-supervised methods was carried out by Hani et al[30] for fruit counting and detection in apple orchards. According to their results, CNN, Faster R-CNN, U-Net, and other Deep Learning algorithms performed worse for yield mapping than traditional methods like Gaussian Mixture Models.In their examination of DL applications for fruit counting and yield estimation, Koirala et al[31] showed the efficiency of Deep Learning methods in extracting crucial features. The authors specifically recommended employing CNN detectors, deep regression, and LSTM approaches for estimating fruit load, highlighting the versatility of these techniques in agricultural contexts. Van Klompenburg et al [32] reported in a systematic literature review on machine learning-based agricultural production prediction that neural networks, in particular, CNNs, LSTM, and Deep Neural Networks, are widely utilized in this domain. The authors highlighted the variability in the number of features employed across studies, emphasizing that certain predictions are reliant on object counting and detection rather than traditional tabular data. Additionally, they observed a diverse landscape in feature selection strategies.

With an emphasis on agricultural diseases, Lee et al [33] developed a self-predictive crop yield platform using Deep Learning techniques. The study found that the CNN algorithm performed better than the R-CNN and YOLO algorithms for the crop disease detection module. The study also demonstrated the performance of the Rectified Linear Unit (ReLU) activation function in obtaining high performance for the Crop Yield Prediction (CYP) module, highlighting the importance of using it in artificial neural networks. Shifting the focus to the integration of DL methods, Chlingaryan et al[34] explored the domain of predicting crop yield and estimating nitrogen status using ML techniques. The findings suggested that advancements in ML, particularly within the domain of Deep Learning, are poised to deliver cost-effective solutions. In a comprehensive review of DL applications in dense agricultural scenes, Zhang et al[35] covered a spectrum of tasks in a survey whichdemonstrated that DL excels in handling dense agricultural environmentsincluding recognition and classification, detection, counting, and yield estimation.

2.4 Ensemble Learning Techniques

This section presents the application of ensemble learning techniques in the domain of crop prediction, showcasing their significance and impact on improving predictive accuracy. Ensemble learning involves combining multiple models to improve the overall performance and robustness. In the context of crop prediction, this approach integrates diverse algorithms, using their collective strength to produce more reliable and accurate predictions. Ensemble techniques, such as bagging and boosting, playan important role in mitigating the limitations of individual models and contribute to creating more resilient and adaptable crop prediction systems. The section explores the methodologies, advantages, and outcomes associated with employing ensemble learning techniques in the context of precision agriculture, shedding light on their role in changing crop prediction models.

Agarwalet al [36], in tackling the complex challenge of precise crop prediction amidst climate variations, proposed an innovative solution utilizing ensemble learning. This methodology involves combining predictions from distinct machine learning algorithms, recognizing the inherent limitations of individual models and aiming to improve accuracy by using the collective strengths of multiple approaches. The authors undertook a training process on a diverse dataset using five different machine learning algorithms, selecting the top performers to construct an ensemble model. This strategic ensemble approach sought to fortify stability and resilience in crop recommendations, acknowledging and accommodating the varied strengths and weaknesses of individual models. The study emphasized that ensemble learning stands out in efficiently managing complex agricultural data, providing a robust framework for evaluation, and holds the potential to improve the efficiency of crop recommendation systems. The overarching goal was to promote improved agricultural practices and higher crop yields, resulting in mutual benefits for both farmers and the nation.Keerthanaet al[37] explored machine learning's role in crop yield prediction, focusing on ensemble techniques for improved accuracy. Their research centred on predicting crop types based on location parameters, utilizing a combination of supervised and unsupervised learning methods. Through a comprehensive search and analysis of data from various sources, the authors finalized 28242 instances with seven key features, emphasizing climatic conditions' relevance. Notably, they experimented with Neural Networks and Decision Tree algorithms, pinpointing the latter's effectiveness. The conclusion highlighted the successful implementation of a crop yield prediction system, specifically showcasing the Ensemble of Decision Tree Regressor with AdaBoost Regressor as a powerful tool to improve accuracy. This system offers practical guidance for farmers in choosing optimal crops based on location and weather conditions, addressing key agricultural challenges.

In keeping with the ambitious Agenda Zero Hunger by 2030, Isaac et al [38] examined the use of tree-based ensemble learning models for crop suitability and production prediction. The study's objectives were to create and evaluate predictive analytics tree-based ensemble learning models, as well as to understand the complex interactions that exist between environmental conditions and crop results. Utilising a Kaggle dataset that was made publicly available, the experimental results demonstrated exceptional model performance, with an accuracy of 99.32%. The ability of gradient tree-based ensemble models, such as XGBoost and LightGBM, to outperform traditional ML models and demonstrate how they may transform crop management strategies for higher yields was especially significant. The study's revelations emphasized the significant impact of factors such as rainfall and potassium levels on the selection of crops within specific regions. The implications of this research extend to furnishing farmers with invaluable decision-making tools, empowering them to optimize resource allocation, fine-tune irrigation schedules, and customize agricultural practices to meet the specific requirements of different crops, ultimately resulting in heightened productivity. The identification of pivotal factors influencing crop growth, including rainfall, potassium, and phosphorus, highlighted the importance of sustainable agricultural practices, advocating for targeted and efficient fertilization strategies with positive environmental repercussions.

2.5. PublicAvailable Datasets

This section presents the various public datasets utilized in the field of crop prediction while some of the Datasets are available on request. Examining the diverse datasets is crucial for understanding the breadth of information that contributes to accurate predictions in agriculture. Researchers and practitioners often rely on these datasets to develop and validate models, incorporating factors such as soil attributes, climate conditions, and historical crop performance. The availability and quality of datasets playa keyrole in crop prediction models, influencing their reliability and applicability across different regions as shown in Table 1.

Table 1.Public Datasets in the Domain of Precision Farming [39]

Reference	Purpose	Number of Objects
[40]	Flower Classification	1360

[41]	Vegetable and Fruit Classification	~160,000
[42]	Species Detection and Classification	~6.6 M
[43]	Pest Detection	18,983 images
[44]	Species Detection and Classification	~49,000
[45]	Object Detection and Instance Segmentation	4432 boxes, 2020 masks
[46]	Robotic Computer Vision Control	7853
[47]	Fruit Detection, Segmentation, Counting	~41,000
[48]	Fruit Detection	1455
[49]	Pest Detection	~264,700
[50]	Fruit Detection and Tracking	~86,000
[51]	Pest Detection	6410 images
[52]	Disease Detection, Tree Counting, Classification, and Segmentation	93
[53]	Grey Mould Detection	121
[54]	Fruit Detection and Tracking	~8000
[55]	Grassland Detection for Agricultural Robotics	15,519

3. Farming

Farming is a deeply ingrained and vital human endeavour, embodying the very essence of our connection to the land and our sustenance. It entails the deliberate and systematic cultivation of crops, the husbandry of livestock, and the stewardship of natural resources with the primary objective of generating sustenance in the form of food, fibre, and an array of essential products crucial for our survival. This enduring practice, deeply woven into the fabric of human history, extends back through millennia, reflecting our innate need to equip the land's resources for nourishment and well-being. The variousdomain of farming entails the judicious management of agricultural resources, the careful allocation of arable land, and the application of a diverse array of farming techniques honed over generations. Through these techniques, farmers skillfully manipulate the environment to encourage the growth of crops and the rearing of livestock, serving as stewards of both the land and the sustenance it yields. In essence, farming transcends its elemental role as a means of sustenance; it symbolizes the enduring partnership between humanity and the earth, embodying the difficult interplay of tradition, innovation, and the inexorable drive to feed, clothe, and nurture our civilizations [56].

Farming can be classified into:

1. Traditional Farming.

2. Modern Farming (Precision Farming).

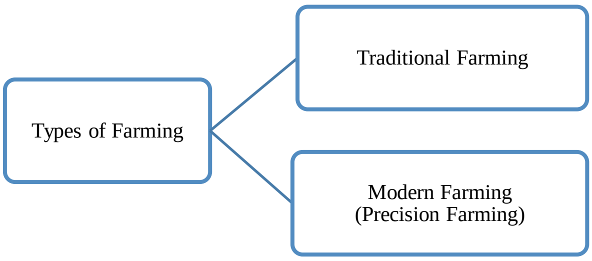


Figure 2. Basic Classification of Farming.

Figure 2 shows the fundamental classification of farming, delineating two primary categories: Traditional Farming and Modern Farming, with the latter encompassing Precision Farming. Traditional Farming represents the conventional, age-old agricultural practices deeply rooted in history, often reliant on manual labour and traditional techniques. In stark contrast, Modern Farming, inclusive of Precision Farming, embodies a paradigm shift marked by the joining of modern techniques and data-driven approaches. Precision Farming, as a subset of Modern Farming, uses advanced technologies, including IoT sensors, Artificial Intelligence, and remote sensing, to optimize agricultural practices. This classification lays the foundation for understanding the evolving landscape of agriculture, spanning from time-honoured traditions to the innovative frontiers of technology-driven farming practices.

3.5. The Traditional Farming Method

Traditional Farming, a time-honoured practice that has sustained communities for generations, represents a cornerstone of global food production. This age-old system is deeply rooted in a series of labour-intensive processes that harmonize with the rhythm of the seasons and the unpredictability of nature. At the heart of traditional agriculture lies the good preparation of fields, where the soil is worked through hours of toil to create fertile ground for crop growth. Seed choice is a decision of paramount importance, where generations of farming wisdom guide the selection of seeds ideally suited to the local climate and soil conditions. The act of planting, or seeding, is performed with care and precision, often by hand, ensuring that each seed finds its place in the earth at the right depth and spacing [57].

In the domain of traditional Farming shown in Figure 3 below, a deep reliance on natural resources is exemplified by the dependence on seasonal rainfall as the primary source of irrigation. The farmer's commitment to the land extends to the application of natural fertilizers, such as compost and animal manure, to enrich the fertility of the soil. Yet, the nurturing of crops is a dual effort, as traditional farmers must also contend with the persistent challenge of unwanted plants, diligently removing weeds that threaten the health of their cherished crops. The agricultural cycle crescendos with the joyous harvest gathering, where the fruits of labour are painstakingly collected using age-old tools like sickles or scythes. The selection of crops to be cultivated reflects the profound connection between traditional agriculture and local communities, as the choice of what to plant is influenced by market demand, local preferences, and the adaptability of crops to the region's specific needs. Traditional agriculture stands as a testament to the resilience and wisdom of generations of farmers who have persevered through the ages, nurturing the land to provide sustenance and nourishment for their communities [58].

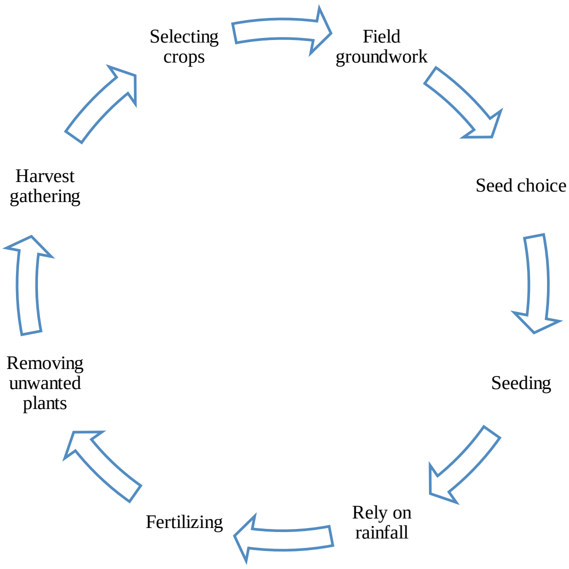


Figure 3. Traditional Farming Process

3.6. The Modern (Precision Farming)Method

With the use of innovative technologies to optimize agricultural practices, precision farming is a paradigm-shifting approach in modern agriculture. It embodies a data-driven approach to cultivation when the agricultural process is precisely regulated in every way, from seed selection to resource management and harvest. The core tenet of precision farming lies in the precise, site-specific understanding of the agricultural landscape, empowering farmers to decide and act with understanding. This method allows real-time monitoring, analysis, and adaptation by utilizing a variety of modern technologies such as remote sensing, IoT devices, GPS, and data analytics. Precision farming is not just an evolution of technology but a fundamental revolution, promising increased yields, reduced resource wastage, and sustainable agriculture, while simultaneously tackling the problems of environmental sustainability and food security in a time of shifting climatic patterns and expanding global population[59].

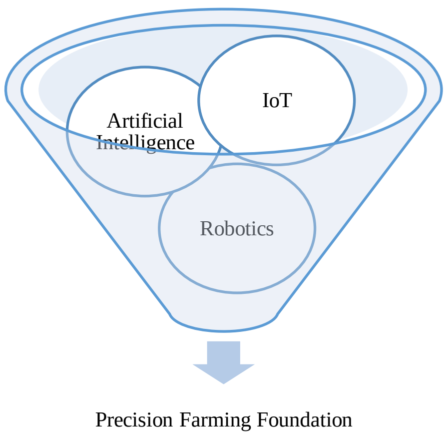


Figure 4. Precision Farming Foundation

Figure 4 shows the key building blocks of the Precision Farming Foundation. Think of it like a toolbox for modern farming. In this toolbox, we have IoT (Internet of Things) devices that collect important data from the farm. Then, there's Artificial Intelligence (like a smart brain) that uses this data to make smart decisions for the farm. Lastly, we have Robotics, which are like helpful farm machines. All these tools work together to help farmers make better choices about crops and resources, making farming more efficient and productive. It's like having a high-tech helper for farmers.

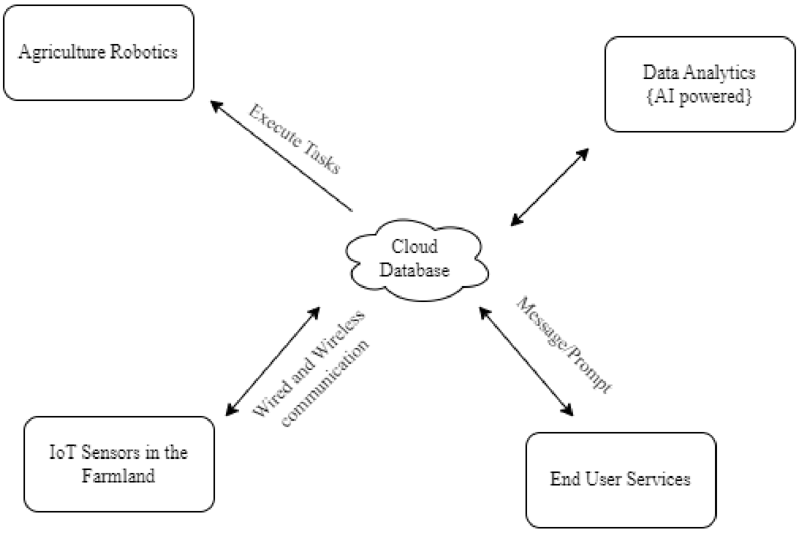


Figure 5. Steps in Precision Farming.

Figure 5 illustrates the sequential steps in Precision Farming, like a recipe for smart farming. It all starts with Agriculture Robotics, which are like high-tech helpers on the farm. These robots carry out tasks and send information to a Cloud Database, which is like a big, smart storage place. Then, Data Analytics, powered by Artificial Intelligence (a smart brain), processes all the information from the farm and makes clever decisions. There are also IOT Sensors (fancy farm sensors) in the fields, wired and wireless, sending data to the same Cloud Database. The Cloud Database is like the heart that connects everything. Finally, the End User Services, which could be farmers or anyone interested, get messages and prompts from the Cloud Database. It's a smart system that helps farms be more efficient and productive, like having a digital farming assistant.

3.6.1. Crop Prediction

Crop prediction, as animportant domain within agricultural science and technology, is a field of paramount importance in the contemporary agricultural landscape. It embodies a sophisticated interdisciplinary approach that melds agronomy, data science, and technology to forecast crop yields, optimize resource allocation, and improve agricultural sustainability. This scientific discipline has gained prominence as a response to the escalating global demand for food, requiring innovative strategies to boost agricultural productivity and mitigate the challenges faced by climate change and resource scarcity. Crop prediction is driven by the premise that data-driven insights can empower decisions on crop selection, planting dates, and resource management should be made by farmers and other agricultural stakeholders with understanding. This introduction serves as the gateway to a comprehensive exploration of the methods, models, and technologies underpinning crop prediction, exploring its various aspects, applications, and implications in the pursuit of sustainable and resilient agricultural systems [60]

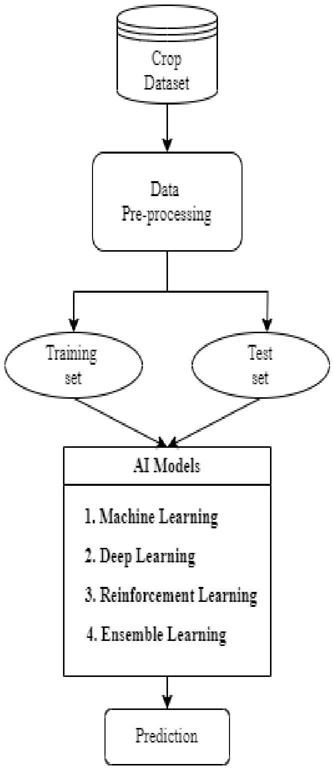


Figure 6. How Artificial Intelligence Techniques AreUsed in Precision Farming

Figure 6. illustrates the step-by-step process of how Artificial Intelligence techniques are equipped within Precision Farming. It all begins with the Crop Dataset, which contains essential agricultural data. This data is then subjected to Data Pre-processing, where it's organized into a Training Set and a Test Set to ensure the AI models receive the right information. The core of this AI-powered system is the AI models block, featuring Machine Learning, Deep Learning, Reinforcement Learning, and Ensemble Learning, each with its unique capabilities. These models analyze the data to make Predictions, helping farmers optimize their crop management, reduce waste, and improve yields, making farming smarter and more efficient.

3.6.2. The Role of Precision Farming in Crop Prediction

The ability of precision farming to provide accurate, site-specific solutions for crop management and decision-making has made precision farming, as a full agricultural management system, more popular in recent years. Using IoT sensors in agricultural areas is the basis of precision farming's crop prediction [61]. These sensors are placed all over the agricultural landscape to gather several data points, such as crop health indicators, weather, and soil moisture levels. This data forms the backbone for predictive modelling.Artificial Intelligence, with its robust data analytics capabilities, plays a key role in crop prediction [62]. AI algorithms are employed to analyze the extensive datasets collected by IoT sensors. The data is scrutinized for patterns, trends, and correlations that are not apparent through traditional methods. AI-powered predictive models are designed to predict crop yields, know the best time to plant, and even detect diseases or pests early.Furthermore, data collecting is aided by remote sensing technologies that provide an aerial perspective of the fields, such as drones and satellite photography. By offering insightful information on crop health and growth, these technologies increase the precision of predictions [63].

4. Performance Analysis of Recent Models for Crop Prediction

This section presents a detailed comparison of the performance of different categories of learning algorithms, specifically ML, DL, reinforcement learning, and ensemble learning. We assess how well these algorithms perform in the context of the study's objectives. This performance analysis is crucial for understanding the suitability of various learning approaches in the given agricultural context. It aids in identifying which algorithms excel in optimizing crop production, reducing waste, and making decisions related to planting, watering, and harvesting crops. We focused only on models developed recently within a 5-year frame (2019-2023) performance analysis.

Table 2. Comparative Analysis of Recent ModelsUsed for Crop Prediction and Precision Farming

Approach	Year	Authors	Algorithm(s)	Accuracy
Supervised learning	(2021)	Pawar et al [64]	NB	95%
	(2019)	Bondre and Mahagaonkar [65]	SVM	99.47%
	(2019)	Mayagopal and Bhargavi [66]	M5 Prime	85%
	(2020)	Mupangwa et al [67]	LR KNN	58% 54%
Unsupervised Learning	(2021)	Pawar et al [64]	K-means	67.875%
Deep learning	(2020)	Muneshwara et al [68]	ANN	98%
	(2020)	Khaki et al [69]	CNN	85.82%
	(2021)	Agarwal and Tarar [70]	RNN LSTM	97% 97%
	(2020)	Kwaghtyo, Dekera Kenneth, and Christopher Ifeanyi Eke et al [71]	ANN	98%
Ensemble learning	(2021)	Suruliandi et al [72]	Bagging	89%
	(2020)	Mishra et al [73]	Adaptive Boost	99.69%

This comprehensive table provides an overview of various approaches in crop prediction using precision farming, highlighting the reference papers, algorithms employed, and the corresponding performance metrics. In supervised learning, Pawar et al[64] utilized the Naïve Bayes algorithm, achieving a Cohen's Kappa Score of 95% accuracy. Bondre and Mahagaonkar [65] employed Support Vector Machines (SVM) with remarkable success, reaching 99.47% accuracy. Mayagopal and Bhargavi [66] implemented the M5 Prime algorithm, yielding an 85% accuracy rate, while Mupangwa et al[67] applied both Linear Regression and k-nearest Neighbors (KNN), resulting in 58% and 54% accuracy, respectively.

In the approach of unsupervised learning, Pawar et al[64] utilized the K-means algorithm, achieving an accuracy of 67.875%. Deep learning approaches showcased promising results, with Muneshwara et al[68] employing ANN for 98% accuracy, Khaki et al[69] using CNN with an 85.82% accuracy rate, and Agarwal and Tarar [70] employing Recurrent Neural Networks and LSTM models, both achieving a high 97% accuracy.

Ensemble learning techniques were also explored, with Suruliandi et al[72] implementing Bagging for an 89% accuracy rate. Mishra et al[73] adopted Adaptive Boosting, achieving a remarkable accuracy of 99.69% with a 100% improvement using Mean Absolute Deviation (MAD) and R2 Score. This detailed summary gave valuable knowledge into the diverse approaches and their corresponding performance outcomes in precision farming for crop prediction.

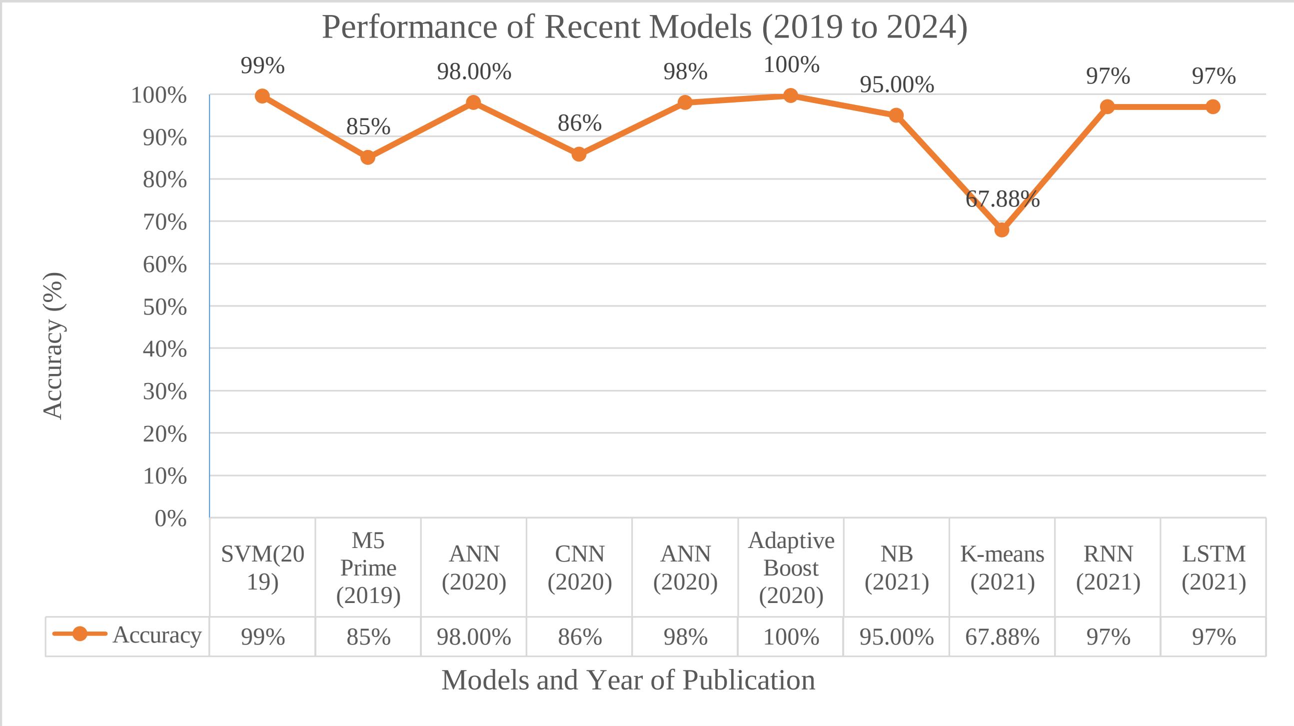


Figure 7. Performance of recent models

Figure 7 illustrates an assessment of the performance of models from the year 2019 to2024 considered in this research. This analysis explores the efficiency of these models, offering informationabout their predictive capabilities and accuracy.

5. Challenges

This section shows the difficulties that come with using precision farming for predicting crop outcomes. These difficulties involve issues like making sure data is accurate, having access to the right technology, and following regulations. Understanding and solving these challenges is crucial for making precision farming work well in agriculture as shown in Figure 8.

1. Data Security and Privacy [74]

In precision farming, a big problem is keeping all the farm information safe and private. Because we use a lot of smart sensors and special technologies that watch the farm, we collect a ton of important data. This data tells us about the soil, and how the crops are doing, and even predicts how much we'll get. But, we need to be careful that this information doesn't get into the wrong hands. There's a worry about hackers and people who shouldn't see this farm info. To fix this, we have to make really strong security plans to protect the data and follow the rules about keeping information safe. This way, we can make sure the farmers' details stay private, and the farm data doesn't end up where it shouldn't. It's a big challenge, but having good security and following the rules helps us solve it.

2. Data Quality and Quantity [75]

Obtaining the right amount of good information from different places is a challenge in precision farming. We use smart sensors, special technologies, and old records to collect this info. But, sometimes, the data we get might not be perfect. It can bemistaken or incomplete. This can cause our predictions about the farm to be wrong. Also, we need a lot of data to make sure our predictions are really good. But, for smaller farms or places with not much data, this can be tough. It's like needing a lot of puzzle pieces to see the whole picture. So, getting the right and enough data is a challenge, especially for smaller farms or places with not many records to use.

3. Technology Accessibility [76]

In certain regions, using advanced technology and stable internet is not so easy because it's not available everywhere. This makes it hard for farmers to use and benefit from precision farming methods. You see, for these methods to work well, we need good technology and fast internet to connect smart sensors and share data. But in some places, they don't have these things, making it tough for farmers to use the latest farming techniques that could help them. It's like having a cool tool but not having all the necessary parts to make it work smoothly. So, the limited access to advanced technology and speedy internet in some regions is a challenge because it slows down the use of precision farming, making it less effective for those farmers.

4. Regulatory Compliance [77]

Following the rules and standards set by the local and national governments about how we use data, manage land, and take care of the environment can be hard for precision farming users. There are many different rules, and they can make precision farming more complicated and expensive. It's like having a lot of different puzzle pieces that need to fit just right. So, sticking to all these rules about how we use data, treat the land, and care for the environment can be a big challenge for farmers using precision farming. It adds extra layers of complexity and can cost more money to follow all the rules correctly.

5. Scalability [78]

A challenge in agriculture is making sure that precision farming methods can work for all kinds of farms, whether they're small family ones or really big commercial ones. Sometimes, the solutions that are good for huge farms don't fit well with smaller, more varied farms. It's like having a tool that works great in a big garden but doesn't fit well in a tiny one with different plants. So, making precision farming work for all farm sizes and types is a challenge because one size doesn't fit all in farming. There is a need for a solution that can adapt to different farm setups and sizes.

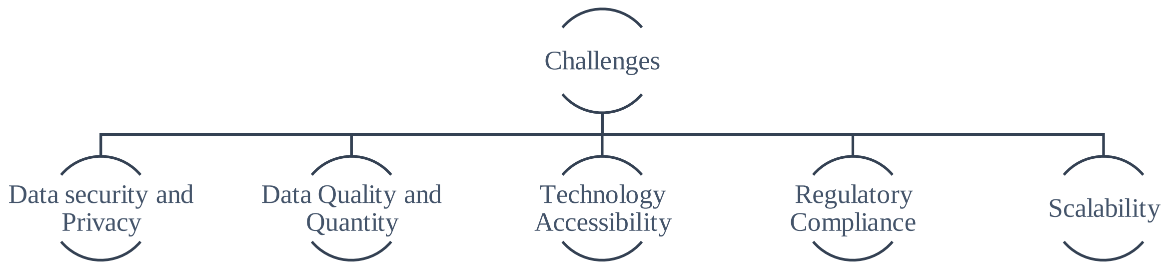


Figure 8. Challenges of Precision Farming

6. Future Prospects of Crop Prediction

In this section, we look ahead to where precision farming is headed in figure 9. This means exploring exciting possibilities like using drones, adapting to climate change, and making agriculture more sustainable. These future paths aim to make farming smarter, more efficient, and better for our planet and food supply.

1. Advanced Robotics and Automation [79]

Promoting the wider adoption of agricultural robots signifies a significant stride towards modernizing various farming operations. These autonomous machines are engineered to undertake a spectrum of tasks, including but not limited to planting, harvesting, and pest control. Their integration into agricultural practices has the capacity to bring about in the future of sustainability and efficiency. By taking over labour-intensive and time-consuming activities, agricultural robots can diminish the dependency on manual labour, contributing to reduced operational costs and greater precision in farming processes. This evolution towards automation not only optimizes resource utilization but also ensures that crops are managed and cultivated with heightened accuracy, promising a more productive and environmentally responsible future for agriculture.

2. Global Data Sharing and Collaboration [80]

Encouraging worldwide collaboration and the open exchange of data within the domain of precision farming represents an important step towards shaping the future of agriculture. This collaborative approach aims to assemble a comprehensive and precise knowledge repository that can empower agricultural decision-makers with a wealth of information. By encouraging global cooperation, stakeholders in the agricultural sector can collectively gather information from diverse regions, climates, and farming practices, yielding a more robust understanding of crop management and resource allocation. The combination of this global knowledge serves as a valuable resource for enhancing precision farming techniques, fine-tuning predictive models, and implementing sustainable practices on a broader scale, ultimately contributing to the global pursuit of food security and environmentally responsible agriculture.

3. Urban and Vertical Farming Integration [81]

Adjusting precision farming techniques for urban and vertical agriculture brings significant benefits by making the most out of resources and lowering the impact on the environment. In these limited spaces, employing data-driven methods helps use resources efficiently, save water, and decrease the overall environmental footprint. This approach aligns with the increasing need for locally sourced, fresh produce while ensuring sustainable practices. Essentially, adapting precision farming for urban and vertical agriculture proves to be an effective strategy for meeting the demand for local, eco-friendly produce.

4. Blockchain for Traceability [82]

Using blockchain technology for end-to-end traceability of agricultural products is a novel approach that changes transparency and trust within the supply chain. By employing blockchain, every step of a product's journey, from farm to fork, is recorded and securely stored. This not only allows consumers to trace the origins and journey of their food but also provides a robust system for verifying the authenticity of products. It ensures that claims of organic, sustainable, or fair-trade practices can be substantiated, promoting consumer confidence. Furthermore, it holds immense potential for food safety by swiftly pinpointing the source of contamination in the event of a recall, safeguarding public health and enhancing the integrity of the entire food industry. In essence, blockchain technology is a transformative force, forging a path towards an era of trust, accountability, and transparency in the agricultural supply chain.

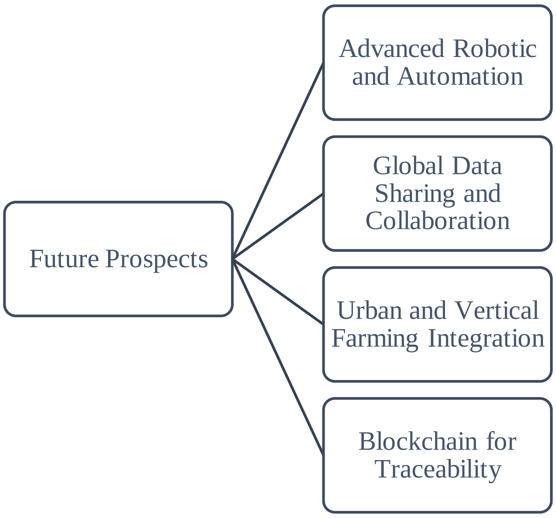


Figure 9. Future Prospects in Precision Farming

7. Conclusion

This study has undertaken a comprehensive exploration of the evolving landscape of crop prediction utilizing precision farming techniques. This aim has unveiled both the promises and intricacies inherent to this dynamic domain. By combining advanced technologies, encouraging collaboration, and advocating global data exchange, precision farming is poised to enact a substantive metamorphosis within the agricultural sphere, encouraging enhanced efficiency, sustainability, and transparency. As the authors of this study, our contribution to this discourse is highlighted by our analytical assessment of extant models and our ability to proffer valuable information into the various challenges and future trajectories of precision farming. Our workshows the transformative capacity of precision farming and its pivotal role in sculpting the forthcoming landscape of agriculture, harmoniously combining technological innovation with ecological responsibility, thus augmenting a more productive, adaptable, and data-informed agricultural sector.

Availability of supporting data

The Authors declare that there is no Dataset or code generated during this research.

Competing interests

The authors of the manuscript declare that there are no competing interests.

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Authors' contributions

Ravi Kumar Munaganuri Data Collection, software, validation, formal analysis,resources, writing original draft preparation.

Yamarthi Narasimha Rao Study Conceptualization & design, methodology,investigation, writing review and editing, supervision.

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