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Harnessing Machine Learning for Transformation in Agricultural Sciences: A Review

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Abstract

The application of machine learning (ML) in agriculture is transforming traditional farming practices, offering innovative solutions for improving efficiency, sustainability, and productivity. ML techniques, including supervised, unsupervised, and reinforcement learning, enable predictive modeling for crop yield estimation, disease detection, and resource optimization. These technologies enhance decision-making processes by integrating diverse datasets from IoT devices, satellite imagery, and field sensors, allowing farmers to manage crops and livestock with greater precision. This review explores the advancements of ML in various agricultural domains, including precision agriculture, climate adaptation strategies, livestock management, and automation. In precision agriculture, ML-driven analytics facilitate site-specific crop management, optimizing irrigation, fertilizer application, and pest control. Additionally, ML-powered weather forecasting models improve agricultural planning by predicting climate-related risks, while reinforcement learning-based irrigation systems contribute to efficient water usage. In livestock farming, ML enhances animal health monitoring, behavior analysis, and disease outbreak prediction, promoting welfare and productivity. Despite its numerous advantages, the adoption of ML in agriculture faces challenges such as data quality issues, interoperability concerns, high costs, and the need for technical expertise. Ethical considerations, including data privacy and the socio-economic impact of automation, must also be addressed to ensure equitable and sustainable agricultural transformations. The future of ML in agriculture lies in the continued integration of big data analytics, IoT devices, and robotics to automate farm operations while minimizing environmental impacts. Research efforts should focus on developing cost-effective, scalable ML solutions accessible to both large-scale agribusinesses and smallholder farmers. By addressing current limitations and leveraging technological advancements, ML can play a pivotal role in shaping the future of agriculture, ensuring food security, sustainability, and resilience in the face of climate change.

Keywords: Machine Learning, Precision Agriculture, Climate Adaptation, Livestock Management, IoT, Big Data, Automation, Sustainable Agriculture.

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1. Introduction

The integration of ML into agricultural practices represents a pivotal shift toward more efficient, sustainable, and productive farming methods (Malhotra and Anand, 2020; Ahmad and Nabi, 2021; Elbehri and Chestnov, 2021; Ersin et al., 2023). By leveraging algorithms and data-driven models, ML can optimize the decision-making process, from seed selection and planting to crop management and harvesting (Table 1). The capability of ML to analyze vast amounts of data—from soil health to weather patterns—enables farmers to make more informed decisions that lead to enhanced yields and reduced environmental impact (Mekonnen et al., 2019; Shaikh et al., 2022; Ersin et al., 2023).

The historical integration of technology in agriculture has been marked by several revolutionary changes, commonly referred to as agricultural revolutions. From the domestication of plants and animals to the development of the plow and crop rotation techniques, each phase has significantly influenced agricultural productivity and societal structures. The introduction of mechanization in the 18th century, followed by the chemical revolution of fertilizers and pesticides in the 20th century, and the more recent adoption of genetically modified organisms (GMOs), all represent critical technological advancements. These innovations have progressively helped to alleviate labor demands and improve crop yields (Moore, 2010; Qaim, 2016). ML represents the latest wave in this ongoing evolution, often considered part of a broader "digital agricultural revolution." (Fink, 2022).

ML's relevance in agriculture can be appreciated through its ability to transform traditional farming into precision agriculture. Precision agriculture uses information technology and a range of data—including data collected from the field by sensors, satellites, or drones—to guide farming decisions (Table 1). ML models can process this data and provide insights at a scale and speed beyond human capabilities. For example, ML algorithms can predict optimal planting times and recommend specific crop varieties that are most likely to thrive in particular environmental conditions (Thilakarathne et al., 2022).

Moreover, ML applications extend beyond crop cultivation to include livestock management, where they enhance capabilities such as health monitoring, diet optimization, and even behavioral predictions (Monteiro et al., 2021; Surana and Sharma, 2024). These applications demonstrate the breadth of ML's impact, streamlining operations and improving outcomes across different farming sectors (Monteiro et al., 2021; Thilakarathne et al., 2022) (Tables 1–4). However, despite the promising advantages of ML in agriculture, there are significant challenges that hinder its widespread adoption (Sharma et al., 2020). Issues such as data collection difficulties, privacy concerns, the need for robust and scalable models, and the integration of these systems into existing agricultural practices pose substantial barriers (Dayoub et al., 2024).

The primary objective of this review paper is to elucidate the various applications of ML in agriculture and assess their impact on the field. By examining specific case studies and existing research, this paper aims to highlight the effectiveness of ML technologies in enhancing various aspects of agriculture. The goal is to provide a comprehensive overview that can serve as a resource for researchers, practitioners, and policymakers involved in agricultural technology.

In conclusion, this review paper will not only showcase the current state of ML applications in agriculture (Table 1) but also discuss future directions and innovations that could further enhance its effectiveness. By providing a detailed examination of both successes and setbacks, the paper aims to paint a realistic picture of what ML can achieve in agriculture and what it will take to fully realize its potential.

2. Machine Learning Basics

ML is a branch of artificial intelligence (AI) that focuses on building systems capable of learning from data, making decisions, and improving over time without being explicitly programmed (Alpaydin, 2020). At its core, ML involves the development of algorithms that can process input data and use statistical analysis to predict an output while updating outputs as new data becomes available. These capabilities make ML particularly valuable in environments requiring rapid analysis and decision-making, such as in agricultural applications (Alpaydin, 2020; Monteiro et al., 2021; Thilakarathne et al., 2022).

The basic premise of ML is that systems can learn from data, identify patterns, and make decisions with minimal human intervention. The process begins with feeding good quality data into a ML model, which then uses statistical techniques to generate insights and predictions. Over time, as the model receives new data, it adapts and refines its predictions or decisions based on what it has learned. This ability to adapt and learn from experience is what distinguishes ML from traditional programmed systems (Table 2).

In agriculture, ML methods can be broadly categorized into three types: supervised learning, unsupervised learning, and reinforcement learning, each serving different purposes and applications.

2.1. Supervised Learning

Supervised learning involves training a model on a labeled dataset, which means that each input data point is paired with an output label. The model learns to map input to output based on this data and can then predict the output for new, unseen data. Supervised learning is commonly used in agriculture for tasks such as disease detection in plants, where images of healthy and unhealthy plants are used to train a model to recognize signs of disease. For example, Liakos et al. (2018) discuss various supervised learning models that have been applied for predicting crop yields and detecting plant diseases.

2.2. Unsupervised Learning

Unsupervised learning differs in that it deals with unlabeled data. The goal here is to explore the data and find some structure within. Common applications in agriculture include clustering and association to find patterns or groupings in data without pre-existing labels. This can be particularly useful for

Table 1. Summary of ML Applications in Agriculture.

Application Area	Description	Key ML Technique(s)	References
Crop Yield Prediction	Using historical and real-time data to predict crop yields	Supervised Learning, CNNs, LSTMs, Random Forest	Khaki and Wang (2019)
Disease Detection	Early detection and diagnosis of plant diseases using image data	CNNs, Deep Learning, Image Processing	Ferentinos (2018)
Pest Management	Identification and quantification of pest infestations	Supervised Learning, CNNs, Deep Learning, Image Processing	Tetila et al. (2020)
Livestock Health Monitoring	Monitoring health and behavior patterns to detect early signs of illness	Time Series Analysis, CNNs, IoT-ML Integration, Predictive Analytics	Surana and Sharma (2024)
Precision Irrigation	Optimizing water usage based on soil moisture and weather forecasts	Reinforcement Learning, IoT-based ML	Yang et al. (2020, 2022) Chen et al. (2021, 2023)
Fertilizer Optimization	Tailoring fertilizer type and quantity to specific crop and soil needs	Supervised Learning	Suchithra and Pai (2020)
Weed Detection	Detecting and classifying weed species in crops for targeted treatment.	Deep Learning, Computer Vision, CNNs	Hasan et al. (2021)
Climate Adaptation Strategies	Forecasting climate impacts and adapting agricultural practices accordingly	Predictive Modeling	Brown and Funk (2008) Ramirez-Cabral et al. (2017)
Robotic Harvesting	Automating the harvesting process using robotic systems; weed control	Reinforcement Learning	Perez-Ruiz et al. (2014, 2018)
Genetic Trait Prediction	Predicting the genetic traits of livestock for optimal breeding outcomes	Supervised Learning	Gonzalez-Recio et al. (2014)
Supply Chain Optimization	Enhance logistics and reduce wastage	Big Data Analytics, Predictive Models	Min (2009)

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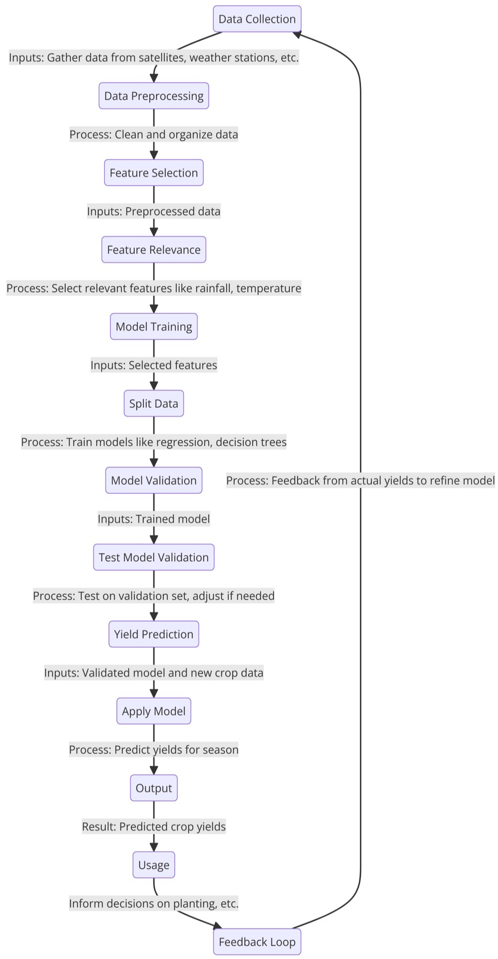

Figure 1. Flowchart of ML algorithm for crop yield prediction.

segmenting different types of crops or soil patterns based on satellite images or sensor data without prior knowledge of the categories. Kamilaris and Prenafeta-Boldu (2018a) provide examples of unsupervised learning used to analyze agricultural data for discovering hidden patterns and relationships.

2.3. Reinforcement Learning

Reinforcement learning is somewhat different, based on the concept of agents learning to make decisions by interacting with an environment. In agriculture, reinforcement learning can be applied to robotic systems such as automated harvesters and drones that learn to navigate and perform tasks more efficiently over time (Yang et al., 2022). The system learns through trial and error, using feedback from its actions to learn behaviors that maximize a reward. An example might include optimizing water use or pesticide application, adapting to varying environmental conditions.

Each of these methods uses different types of algorithms and techniques. For instance, common supervised learning algorithms include decision trees, support vector machines (SVM), and neural networks, while unsupervised learning may use k-means clustering or principal component analysis (PCA). Neural networks, particularly those forming deep learning architectures, are a prominent subset of ML used extensively in advanced image and speech recognition tasks (Doshi et al., 2022).

Deep learning, a complex architecture of neural networks, has shown significant promise in handling vast amounts of data and complex patterns, making it suitable for image-based monitoring of crop and soil health, where large datasets of field images are analyzed to detect anomalies and predict crop performance (Ngugi et al., 2024). Zhang and Kovacs (2012) highlight the application of convolutional neural networks, a type of deep learning, in processing satellite imagery for precision agriculture.

As ML technology continues to evolve, the potential for more sophisticated applications in agriculture increases. However, the successful implementation of these technologies also hinges on overcoming challenges related to data quality, availability, and the interpretability of ML models. As highlighted by several studies, advancing ML in agriculture not only promises increased operational efficiency but also poses questions about best practices in data handling and algorithmic decision-making (Mulla, 2013; Brown and Funk, 2008; Jorvekar et al., 2024).

In conclusion, ML offers powerful tools for enhancing agricultural productivity and sustainability. By automating complex decision-making processes and analyzing large datasets, ML technologies can lead to significant advancements in how food is grown, harvested, and managed. The ongoing research and development in this field are set to redefine traditional agricultural practices, making them more aligned with the digital age.

3. Crop Management

ML has increasingly become a pivotal tool in the domain of crop management, offering transformative solutions ranging from yield prediction to disease management and resource optimization (Gil and Banday, 2024). By leveraging ML techniques, agricultural professionals can enhance efficiency, increase yields, and reduce environmental impacts (Figures 1–6).

3.1. Yield Prediction

One of the most significant applications of ML in agriculture is in crop yield prediction (Figure 1). ML models can analyze various factors including weather data, soil quality, crop type, and historical yield data to predict future crop performance (Chlingaryan et al., 2018). This predictive capability allows farmers to make better-informed decisions about planting and resource allocation. For example, Khaki and Wang (2019) demonstrated the use of ML models to predict corn yield based on environmental and management factors. Their work illustrates how ML can integrate diverse data streams to provide accurate yield forecasts (Table 1) (Khaki and Wang, 2019).

3.2. Advanced Techniques in Yield Prediction

Beyond traditional models, deep learning approaches have been applied to enhance the accuracy of yield predictions. Convolutional Neural Networks (CNNs), for instance, are used to process satellite images and aerial photographs of fields to assess crop health and predict yields. This approach can capture subtle nuances in crop appearance that correlate with yield outcomes (Kamilaris and Prenafeta-Boldu, 2018b; Kattenborn et al., 2021). Another study used CNNs to analyze satellite imagery, successfully predicting crop yields at scale and with notable precision (Lu et al., 2019).

3.3. Disease Detection

ML also plays a crucial role in crop disease detection. By analyzing images of crops captured by drones or handheld devices, ML algorithms can identify disease symptoms early and accurately. This early detection is crucial for preventing widespread outbreaks that can severely impact yields (Table 1) (Ferentinos, 2018; Ahmed and Yadav, 2023; Abbas et al., 2023).

3.4. Pest Management

Like disease detection, ML can be employed to manage pest infestations effectively. By processing images from camera traps or drones, ML models can identify pest species and infestation levels, enabling timely and precise interventions. This reduces the need for broad-spectrum pesticide use, promoting more targeted and environmentally friendly pest control methods (Behmann et al., 2015; Karar et al., 2021; Adetunji et al., 2023; Kariyanna and Sowjanya, 2024).

3.5. Water Resource Optimization

ML algorithms significantly contribute to water resource management in agriculture by predicting the optimal amounts of irrigation required. These models consider weather forecasts, soil moisture levels, and plant water needs

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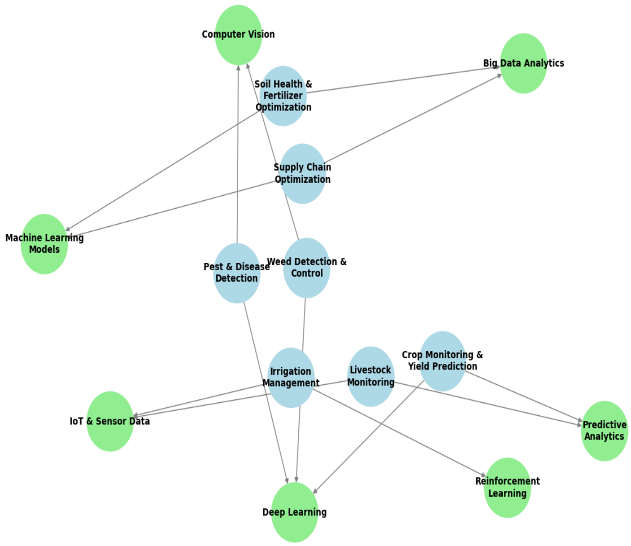

Figure 2. ML applications in Agriculture.

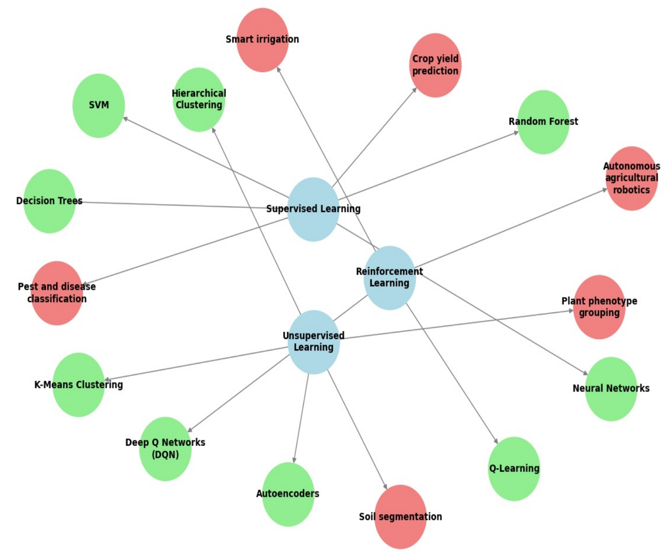

Figure 3. Comparison of ML Techniques in Agriculture.

to recommend irrigation schedules that prevent both under-watering and water wastage (Krishnan et al., 2022; Drogkoula et al., 2023; Ahmed et al., 2024).

3.6. Fertilizer Use Efficiency

Optimizing fertilizer use is another critical application of ML in crop management. Algorithms can predict the most effective fertilizer types, quantities, and application timings based on soil nutrient status and crop requirements. This tailored approach ensures that plants receive exactly what they need for optimal growth, avoiding the excess runoff that can cause environmental damage (Suchithra and Pai, 2020; Wen et al., 2022; Ennaji et al., 2023; Musanase et al., 2023; Islam et al., 2023).

3.7. Integration of Multiple Data Sources

The strength of ML in crop management often lies in its ability to integrate multiple data sources, such as soil sensors, weather stations, and satellite images, to provide a comprehensive view of agricultural systems. This integrated approach enables more precise predictions and better farm management decisions (Saiz-Rubio et al., 2020; Benos et al., 2021; Fuentes-Penailillo et al., 2024).

3.8. Challenges and Future Directions

Despite these advancements, the application of ML in crop management faces challenges, including data collection difficulties, the need for high-quality, labeled datasets, and the adaptation of models to local contexts (Williamson et al., 2021; Araujo et al., 2023). Future research must address these challenges to fully realize the potential of ML in agriculture (Sun and Scanlon, 2019; Williamson et al., 2021; Araujo et al., 2023).

3.9. Sustainability and ML

Lastly, the role of ML extends to enhancing sustainability in agriculture. By optimizing resource use and improving yield predictions, ML helps in reducing the ecological footprint of farming practices. The ongoing development of ML models aimed at sustainable practices is vital for meeting global food demands while protecting the environment (Sharma et al., 2020; Araujo et al., 2023; Hassan et al., 2023a).

4. Livestock Farming

ML is reshaping the landscape of livestock farming by providing advanced tools for monitoring health and behavior, as well as optimizing breeding and production processes. These innovations offer significant benefits in terms of animal welfare, farm efficiency, and productivity (Gonzalez-Recio et al., 2014; Garcia et al., 2020; Neethirajan and Kemp, 2021; Surana and Sharma, 2024; Vlaicu et al., 2024; Talebi and Nezhad, 2024).

4.1. Health Monitoring

One of the primary applications of ML in livestock farming is health monitoring. By using sensors to collect data on various physiological and behavioral indicators, such as body temperature, activity levels, and feeding patterns, ML models can detect early signs of illness or stress in animals. This proactive approach allows farmers to address health issues before they become severe, reducing mortality rates and improving overall herd health (Neethirajan, 2020; Debauche et al., 2021; Layton et al., 2023; Surana and Sharma, 2024).

4.2. Behavior Analysis

Beyond health monitoring, ML is also employed to analyze and understand livestock behavior. This analysis can indicate well-being and help manage animals more effectively. By tracking movements and behavior patterns, ML algorithms can identify abnormal behaviors that signify stress, discomfort, or disease (Kamat and Nasnodkar, 2018; Gomez et al., 2021; Debauche et al., 2021; Hassan et al., 2023b).

4.3. Predictive Models in Breeding

In breeding programs, ML models are used to predict the genetic qualities of offspring, thereby optimizing breeding decisions. These models analyze genetic data alongside phenotypic traits to forecast the breeding values of animals. This approach enhances genetic gains and improves traits like milk yield, growth rates, and disease resistance (Wang et al., 2022; Chafai et al., 2023). Recent studies applied ML techniques to dairy cattle breeding and demonstrated significant improvements in predictive accuracy for milk production traits (Mota et al., 2021; Alwadi et al., 2024).

4.4. Production Optimization

ML also aids in optimizing overall livestock production. By analyzing data on feed intake, growth rates, and environmental conditions, ML models can recommend adjustments to enhance productivity (Biase et al., 2022; Dayoub et al., 2024; Akintuyi, 2024). Other studies showed that ML could optimize feeding strategies to maximize milk yield in dairy cows by predicting individual nutritional needs based on metabolic data (Xu et al., 2019; Giannuzzi et al., 2022; Akintan et al., 2025).

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Table 2. Traditional vs. ML-Based Farming Approaches.

Aspect	Traditional Approach	ML-Based Approach
Decision Making	Experience-based, manual decisions	Data-driven, AI-assisted decision making
Resource Utilization	Fixed resource allocation, often inefficient	Optimized resource allocation using real-time data
Pest & Disease Management	Reactive treatment, high dependency on chemicals	Proactive prevention using predictive analytics
Irrigation Control	Manual irrigation, based on fixed schedules	Automated, precision irrigation based on real-time needs
Yield Prediction	Historical trends, rough estimation	Real-time monitoring with high accuracy
Cost Efficiency	Higher costs due to inefficiency	Reduced costs through optimization
Scalability	Limited scalability due to manual efforts	Highly scalable with automated systems

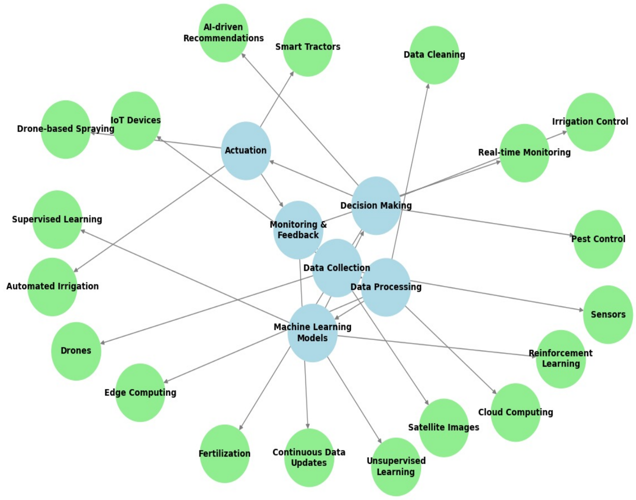

Figure 4. ML-Driven Precision Agriculture System.

4.5. Disease Outbreak Prediction

Another critical application of ML in livestock farming is the prediction of disease outbreaks. By analyzing historical data on disease incidents along with real-time health monitoring data, ML models can predict potential outbreaks and their spread within a herd. This capability allows for timely interventions to contain diseases and minimize impact (Chae et al., 2018; Astill et al., 2018; Ziaur-Rahman et al., 2023). Punyapornwithaya et al. (2022) successfully used ML to predict and manage outbreaks of foot-and-mouth disease, illustrating the potential of these models in managing livestock diseases effectively.

4.6. Integration with IoT

The integration of ML with the Internet of Things (IoT) technologies is a growing trend in livestock management. IoT devices collect vast amounts of data from farm operations, which ML models analyze to provide insights into animal health, behavior, and productivity. This integration enables more automated and precise farming operations (Akhigbe et al., 2021; Ojo et al., 2022; Zafar, 2024). IoT technologies have also been used in supply chain optimization to enhance logistics and reduce wastage (Min, 2009; Kaloxylos et al., 2013; Verdouw et al., 2016; Sharma et al., 2020) (Table 1).

4.7. Challenges and Ethical Considerations

Despite the advancements, the application of ML in livestock farming is not without challenges. Issues such as data privacy, ethical considerations regarding animal monitoring, and the need for robust, fault-tolerant systems are critical concerns (Hamadani et al., 2023; Shekhar et al., 2024). Moreover, the implementation of these technologies must be done thoughtfully to ensure they benefit both animals and farmers without compromising ethical standards.

4.8. Sustainability and Efficiency

ML applications also contribute to the sustainability of livestock farming by optimizing resource use and reducing waste (Lakhouit et al., 2025). For instance, efficient feeding algorithms not only improve animal health but also reduce feed waste and the environmental impact of farming operations (Akintan et al., 2025). This alignment of productivity with sustainability goals is crucial for the future of farming.

4.9. Future Trends

Looking ahead, the future of ML in livestock farming will likely see more advanced analytics, with a greater emphasis on integrating diverse data sources for even more sophisticated insights. As technology continues to evolve, the capabilities and applications of ML in enhancing livestock management will also do so.

In conclusion, ML offers significant opportunities to revolutionize livestock farming. From improving animal health and welfare to optimizing production processes, the benefits of ML in this field are profound. As these technologies continue to develop and become more accessible, they promise to enhance the efficiency and sustainability of livestock operations worldwide, ultimately leading to a more productive and ethical agricultural industry.

5. Precision Agriculture

Precision agriculture is an approach to farm management that uses information technology to ensure that crops and soil receive exactly what they need for optimum health and productivity. The role of ML in precision agriculture (Table 3) is rapidly evolving, becoming integral in enabling site-specific crop management practices that significantly enhance efficiency and yield (Zhang and Kovacs, 2012; Mulla, 2013; Shafi et al., 2019; Monteiro et al., 2021).

5.1. ML and Site-Specific Crop Management

ML facilitates the implementation of site-specific crop management by analyzing data from various sources to make precise decisions about planting, watering, fertilizing, and harvesting (Gorai et al., 2021; Thilakarathne et al., 2022). ML algorithms can process complex datasets to identify variability within fields regarding soil composition, moisture levels, and crop health, allowing farmers to apply tailored treatments rather than uniform applications across entire fields. Mulla (2013) provides an overview of how ML models utilize spatial data to enhance decision-making in precision agriculture.

5.2. Use of Drones

Drones are a critical technology in precision agriculture, equipped with sensors and cameras to collect detailed images and data from above the crop canopy (Daponte et al., 2019; Raj et al., 2020). ML algorithms analyze this data to assess crop health, identify weed infestations, and detect areas of stress such as drought or nutrient deficiency. Drone technology enables rapid, repeated monitoring of fields, offering data that can be immediately acted upon. Sarvakar and Thakkar (2024) discuss the integration of drone-captured imagery with ML algorithms to monitor crop vigour and health efficiently.

5.3. Satellite Imagery in Agriculture

Satellite imagery provides another valuable data source for precision agriculture. With advances in satellite technology, images can now be obtained with greater frequency and resolution, allowing for detailed observations of agricultural land over time (Mulla, 2013; Zhang et al., 2020). ML models use these images to track changes in crop health, predict yields, and even guide irrigation practices. Sharifi (2020) explore the use of satellite images processed with ML techniques to analyze crop biomass and predict yields.

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Table 3. ML Techniques and their Applications in Agriculture.

ML Technique	Example Algorithms	Agricultural Applications
Supervised Learning	Decision Trees, Random Forest, SVM, Neural Networks	Crop yield prediction, Pest and disease classification
Supervised Learning	CNNs, LSTMs, Naive Bayes	Image-based disease detection, Weed identification
Supervised Learning	Gradient Boosting, K-Nearest Neighbors	Soil nutrient prediction, Weather forecasting
Unsupervised Learning	K-Means Clustering, Hierarchical Clustering	Soil segmentation, Plant phenotype grouping
Unsupervised Learning	Principal Component Analysis (PCA), Autoencoders	Feature selection for predictive modeling, Data compression
Unsupervised Learning	Self-Organizing Maps (SOMs)	Pattern recognition in soil types and crop distributions
Reinforcement Learning	Q-Learning, Deep Q Networks (DQN)	Smart irrigation control, Livestock movement optimization
Reinforcement Learning	Policy Gradient, Actor-Critic Methods	Autonomous agricultural robotics, Precision pesticide spraying

5.4. Predicting Weather Impact

ML is also essential in predicting the impact of weather on crop production. By analyzing historical weather data and current forecasts with crop performance data, ML models can predict how changes in weather will affect crop health and growth (Filippi et al., 2019; Elbasi et al., 2023). This information can help farmers make proactive decisions to mitigate risk due to adverse weather conditions. Kumari and Muthulakshmi (2024) highlight how ML can integrate weather predictions with crop data to improve agricultural practices.

5.5. Soil Health Monitoring

Another application of ML in precision agriculture is in monitoring soil health. Sensors embedded in the soil provide data on moisture, pH levels, and nutrient content, which ML algorithms analyze to assess soil health and predict future changes (Kashyap and Kumar, 2021; Folorunso et al., 2023; Jain et al., 2024). This technology enables farmers to manage soil conditions proactively, optimizing conditions for plant growth. Padarian et al. (2020) detail the application of ML models in interpreting soil sensor data to guide management decisions.

5.6. Resource Optimization

ML aids in optimizing the use of resources like water and fertilizers. By analyzing data from soil and crop sensors, ML models can recommend precise amounts of irrigation and fertilizer needed at different field locations, reducing waste and enhancing crop growth (Abioye et al., 2023; Senapaty et al., 2023). Adeyemi et al. (2018) demonstrated how ML models could optimize irrigation schedules based on soil moisture data to conserve water and improve yield.

5.7. Weed Detection

ML algorithms also assist in detecting and classifying weed species within crops. Drones or on-the-ground robots equipped with cameras capture images that ML models process to identify weed species, allowing for targeted herbicide applications (Hasan et al., 2021; Islam et al., 2021; Menshchikov and Somov, 2022; Ehrampoosh et al., 2024). This selective approach reduces herbicide use and minimizes environmental impact. Garibaldi-Marquez (2024) developed a deep learning-based vision system for real-time weed detection and control in cornfields. By creating and annotating a dataset of RGB and multispectral images, they trained both convolutional neural networks (CNNs) and transformer models, with transformers achieving superior weed segmentation performance. The implementation of this system in a Smart Weed Sprayer led to a 45.64% reduction in herbicide usage compared to conventional methods, while maintaining similar weed control effectiveness (Garibaldi-Marquez, 2024).

5.8. Yield Estimation

Accurate yield estimation is crucial for effective farm management. ML techniques utilize data from various sources, including field sensors, drones, and satellites, to estimate crop yields before harvest (Maimaitijiang et al., 2020; Joshi et al., 2023). This estimation helps farmers plan for storage, marketing, and future crop management practices. Khaki and Wang (2019) provide insights into how ML models are developed to predict corn yields using environmental and on-field data.

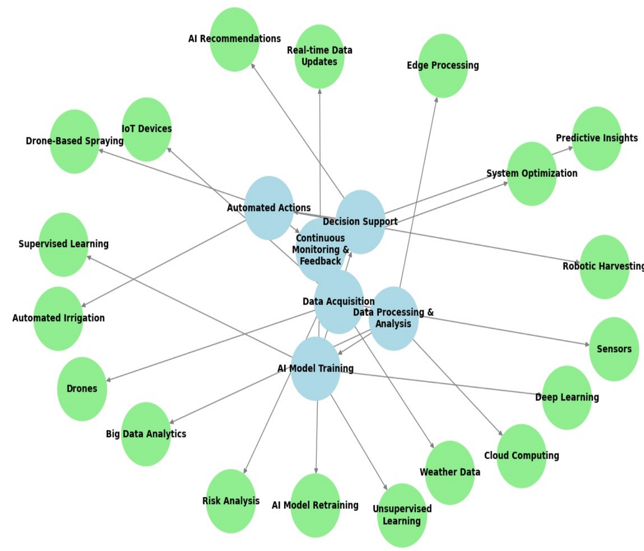

Figure 5. Workflow of an AI-Powered Smart Farming System.

5.9. Integration of Data Sources

The strength of ML in precision agriculture often comes from its ability to integrate and analyze data from multiple sources. This holistic view enables more accurate predictions and recommendations, driving efficiencies across all aspects of farm management (Araujo et al., 2023; Barbosa et al., 2024). Zhang et al. (2020) discuss the integration of different data types, from drones, satellites, and sensors, using ML to create comprehensive models that manage agricultural operations effectively.

5.10. Challenges and Future Prospects

Despite the promising advancements, precision agriculture faces challenges such as data management, the high cost of technology, and the need for specialized knowledge to interpret ML outputs. Future research must address these issues to make precision agriculture more accessible and practical for all farmers (Sharma et al., 2020; Williamson et al., 2021; Araujo et al., 2023; Jorvekar et al., 2024).

In conclusion, ML in precision agriculture represents a frontier in modern farming, offering unprecedented precision in crop management and resource use. As technology advances, it promises to bring even greater efficiencies, enhancing sustainability and productivity in the agricultural sector.

6. Smart Farming

Smart farming, also known as digital or precision farming, integratesML, the Internet of Things (IoT), big data analytics, robotics, and automation to enhance agricultural productivity, sustainability, and resource efficiency (Figure 5). By leveraging real-time data from sensors, drones, and satellite imagery, ML algorithms optimize decision-making processes, reducing waste and improving

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Table 4. Benefits and Challenges of ML use in Agriculture.

Aspect	Benefits/Challenges
Improved Efficiency	Automates tasks like irrigation, pest control, and harvesting, reducing manual labor.
Precision Agriculture	Optimizes water, fertilizers, and pesticides, reducing waste and environmental impact.
Early Disease Detection	ML models detect crop diseases early, preventing major losses and ensuring food security.
Cost Reduction	AI-powered resource allocation minimizes costs related to fertilizers, water, and labor.
Data Dependency	ML models require large datasets; insufficient or biased data can lead to poor results.
High Initial Investment	High costs for implementing AI-powered equipment and software limit adoption.
Limited Access to Technology	Small-scale farmers may lack access to ML tools and infrastructure.
Need for Expert Knowledge	ML models require specialized knowledge to interpret and fine-tune, creating a skills gap.

yields (Wolfert et al., 2017). Smart farming is transforming both crop and livestock management, making agriculture more data-driven, climate-resilient, and economically viable (Kamilaris et al., 2017, 2018a,b).

6.1. IoT-Enabled Smart Farming

The Internet of Things (IoT) is integral to smart farming, enabling real-time data collection and communication across agricultural systems (Figure 5). IoT sensors monitor soil moisture, weather conditions, nutrient levels, and pest activity, transmitting data to cloud-based ML models for predictive analysis (Ray, 2017). This connectivity enhances efficiency and sustainability by supporting smart irrigation, where ML-driven systems automate water usage based on weather forecasts and soil conditions (Zhang et al., 2019). In livestock farming, wearable IoT devices track animal behavior and health, enabling early disease detection and improved welfare (Monteiro et al., 2021). Additionally, precision fertilization utilizes IoT-enabled soil sensors to optimize nutrient application, reducing waste and environmental impact (Islam et al., 2023).

6.2. Big Data and AI in Smart Farming

The vast data generated by IoT devices in agriculture requires big data analytics and AI-driven insights to extract meaningful patterns. Cloud computing and edge AI enable real-time processing, improving yield forecasting, pest control, and market analysis (Verdouw et al., 2016). AI models analyze historical weather data, soil properties, and crop performance to enhance yield predictions (Moore and Lobell, 2015). ML-driven computer vision detects early signs of crop diseases and pest infestations, enabling proactive intervention (Hasan et al., 2021; Sarvakar and Thakar, 2024). Additionally, AI-powered platforms optimize market demand forecasting and supply chain logistics, reducing waste and improving efficiency (Wolfert et al., 2017).

6.3. Automation and Robotics in Smart Farming

The integration of robotics and autonomous systems is transforming farm operations by reducing labor costs and increasing efficiency. AI-powered drones, autonomous tractors, and robotic harvesters perform precise, automated fieldwork with minimal human input (Bac et al., 2014). Autonomous tractors equipped with GPS perform plowing, seeding, and harvesting with high precision, reducing manual labor (Islam et al., 2023). AI-driven robotic weed control systems detect and eliminate weeds without excessive herbicide use, supporting sustainable farming practices (Hasan et al., 2021; Sarvakar and Thakar, 2024). Drone-based crop monitoring, using multispectral imaging and ML models, provides real-time crop health assessments, enabling optimized interventions (Ray, 2017).

6.4. Sustainable and Climate-Resilient Smart Farming

Smart farming technologies enhance sustainability and climate resilience by integrating AI-driven climate models and weather forecasting tools, helping farmers anticipate extreme weather, droughts, and shifting precipitation patterns (Liakos et al., 2018). AI-powered irrigation optimizes water use, reducing waste by 30-50% (Liakos et al., 2018; Kamilaris and Prenafeta-Boldu, 2018). Precision agriculture techniques, such as targeted fertilizer and pesticide application, lower GHG emissions and prevent soil degradation (Tilman et al., 2011). Additionally, ML models predict optimal planting schedules and identify drought-resistant crop varieties, strengthening climate adaptation strategies (Brown and Funk, 2008).

6.5. Challenges and Future Directions in Smart Farming

Despite its numerous advantages, smart farming faces significant challenges related to high costs, technical complexity, data privacy, and accessibility, particularly for smallholder farmers (Schimmelpfennig, 2016). The adoption of IoT devices, AI-driven analytics, and automation often requires substantial financial investment, making it less accessible for smaller farms. Additionally, concerns about data security and standardization continue to hinder widespread implementation.

One major barrier is the high initial investment required for IoT infrastructure, AI-powered analytics platforms, and automation technologies. Many small and mid-sized farms struggle to afford precision agriculture tools, limiting the scalability of smart farming solutions (Rotz et al., 2019). Another critical issue is data privacy and security—the growing reliance on IoT devices and cloud-based analytics raises concerns about farmer data ownership, cybersecurity risks, and potential misuse by third parties (Van der Burg et al., 2021). Furthermore, limited accessibility for smallholder farmers remains a concern, as most ML-driven solutions are designed for large-scale commercial farms, leaving smaller agricultural operations at a disadvantage (Kamilaris et al., 2017, 2018a,b).

To overcome these challenges, future research should focus on developing affordable IoT and AI solutions that are scalable and cost-effective, ensuring broader accessibility across different farming communities (Wolfert et al., 2017). Additionally, interoperability and standardization of agricultural AI systems must be prioritized to enable seamless data exchange across different platforms and devices (Stone & Gilbert, 2018). Lastly, enhancing ML models for sustainability-driven applications, such as carbon-neutral farming and eco-friendly resource management, will be crucial for addressing climate challenges and ensuring the long-term viability of smart farming (Foley et al., 2011).

7. Climate Adaptation Strategies

Adapting agricultural practices to the rapidly changing climate conditions is a pressing challenge that requires innovative strategies. ML offers significant potential in developing predictive models that can help farmers adjust their practices to mitigate the effects of climate variability and extreme weather events (Liakos et al., 2018; Kamilaris and Prenafeta-Boldu, 2018). The application of ML in climate adaptation strategies includes forecasting models that predict weather impacts and optimizing agricultural responses to these predictions (Sharma et al., 2020; Van Klompenburg et al., 2020).

7.1. Predictive Modeling for Climate Adaptation

ML can develop predictive models that simulate various climate scenarios and their potential impacts on agriculture. These models analyze historical climate data and current trends to forecast future conditions, helping farmers prepare for changes in temperature, precipitation, and other climatic factors (Liakos et al., 2018; Kamilaris and Prenafeta-Boldú, 2018). Other studies discuss the use of statistical models in predicting the effects of temperature and rainfall changes on crop yields, enabling adjustments in crop selection and management practices (Lobell and Burke, 2010; Lobell and Gourdji, 2012).

7.2. Weather Forecasting Models

ML models are particularly adept at enhancing weather forecasting techniques, which are crucial for agricultural planning. By processing vast datasets from weather stations and satellites, ML algorithms can predict localized weath-

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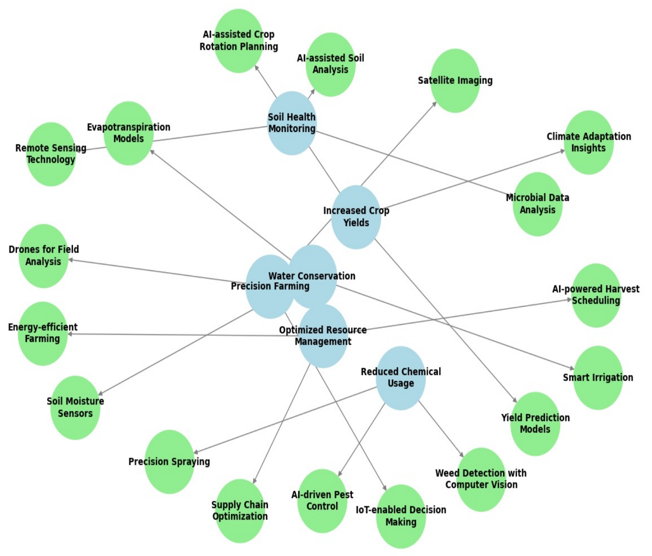

Figure 6. Impact of ML on Sustainable Agriculture.

er events with high accuracy (Liakos et al., 2018; Kamilaris and Prenafeta-Boldu, 2018). Such forecasts allow farmers to make timely decisions about planting, harvesting, and applying inputs like irrigation and fertilizers. A study by Chen et al. (2023) illustrates how ML-enhanced forecasts can significantly improve the accuracy of weather predictions, directly benefiting agricultural scheduling and resource use (Chen et al., 2023).

7.3. Drought Management

Drought is one of the most challenging aspects of climate variability for agriculture. ML models help predict drought conditions well in advance, allowing farmers to implement water-saving measures and choose drought-resistant crop varieties. These models utilize data from soil moisture sensors, satellite imagery, and meteorological data to forecast water availability and crop stress (Liakos et al., 2018; Kamilaris and Prenafeta-Boldu, 2018). AghaKouchak et al. (2015) demonstrate how integrating ML techniques with drought indices can provide early warnings and management strategies for agricultural water use.

7.4. Heat Stress Management

Rising temperatures can lead to heat stress in plants and animals, adversely affecting productivity. ML models can predict heat waves and provide recommendations for managing heat stress, such as modifying planting schedules, selecting heat-tolerant varieties, and implementing cooling systems in livestock facilities (Liakos et al., 2018; Kamilaris and Prenafeta-Boldu, 2018). Rashamol et al. (2019) explore the use of ML in predicting livestock heat stress and suggest management strategies that can mitigate the impact on animal health and productivity.

7.5. Optimizing Irrigation

Climate change often leads to unpredictable rainfall patterns, making efficient water management crucial. ML algorithms analyze weather predictions, soil moisture levels, and crop water requirements to optimize irrigation systems (Liakos et al., 2018; Kamilaris and Prenafeta-Boldu, 2018). These models ensure that crops receive adequate water without wastage, adapting to the changing climate conditions. Ding and Wan (2024) introduce DRLIC (Deep Reinforcement Learning for Irrigation Control), a system designed to enhance irrigation efficiency. By leveraging deep reinforcement learning techniques, DRLIC aims to optimize water usage in agricultural settings, thereby improving crop yields and promoting sustainable water management practices (Ding and Wan, 2024).

7.6. Pest and Disease Forecasting

Changes in climate also influence the prevalence and distribution of pests and diseases. ML models can predict these changes by analyzing climatic factors and landscape data, allowing for timely and targeted pest and disease control measures (Liakos et al., 2018; Kamilaris and Prenafeta-Boldu, 2018). This reduces the reliance on chemical pesticides and helps maintain crop health. Other studies discussed the development of ML models that forecast plant disease outbreaks based on climate data, helping farmers prevent widespread crop damage (Fenu and Malloci, 2021; Domingues et al., 2022; Wadhwa and Malik, 2024).

7.7. Yield Prediction Under Variable Climates

ML models are crucial for predicting crop yields under changing climate conditions. These models consider variables such as temperature fluctuations, rainfall, and extreme weather events to provide farmers with realistic yield forecasts (Liakos et al., 2018; Kamilaris and Prenafeta-Boldu, 2018). This information is vital for planning and can help in risk management and crop insurance assessments. Ramirez-Cabral et al. (2017) present an ML approach that incorporates climate projections to forecast yield impacts, aiding in long-term agricultural planning (Table 1).

7.8. Adaptive Crop Management Tools

Advanced ML tools can integrate various climate adaptation strategies, providing a comprehensive platform for farmers to manage their crops under changing climatic conditions. These tools analyze data from multiple sources, offering recommendations for planting times, crop rotations, and soil management practices (Liakos et al., 2018; Kamilaris and Prenafeta-Boldu, 2018). Other studies explore how such integrated systems can support farmers in adapting their operations to future climates, promoting resilience and sustainability (Adamides et al., 2020; Delfani et al., 2024; Amiri et al., 2024).

7.9. Challenges and Future Directions

While ML presents numerous opportunities for climate adaptation in agriculture, challenges remain, particularly in data availability, model accuracy, and the interpretation of complex ML outputs (Liakos et al., 2018; Kamilaris and Prenafeta-Boldu, 2018). Future research needs to focus on enhancing the robustness of ML models and ensuring they are accessible to farmers worldwide, including those in developing countries (Araujo et al., 2023; Elbasi et al., 2023). In conclusion, ML offers a promising toolkit for developing climate adaptation strategies in agriculture. By providing accurate predictions and actionable insights, ML enables farmers to anticipate and respond effectively to climatic changes, thereby reducing risks and optimizing agricultural productivity. The continued evolution of these technologies is likely to play a critical role in shaping the future of sustainable farming in an era of climate uncertainty.

8. Challenges and Future Directions

The adoption of ML in agriculture has ushered in a new era of efficiency and productivity. However, the path to fully leveraging ML technologies comes with significant challenges that need to be addressed to ensure its effective integration and sustainability (Liakos et al., 2018; Kamilaris and Prenafeta-Boldu, 2018). Additionally, exploring future directions and potential research areas is crucial to advancing these technologies in agricultural practices (Araujo et al., 2023; Elbasi et al., 2023).

8.1. Data Availability and Quality

One of the primary challenges in applying ML in agriculture is the availability and quality of data. High-quality, large datasets are fundamental for training robust ML models. In many agricultural settings, especially in developing countries, collecting comprehensive and accurate data can be difficult due to limited technological infrastructure and resources. Ensuring the availability of reliable datasets is essential for the development of effective ML applications in agriculture (Table 1). Several studies discuss the importance of data quality and availability in training ML models for predicting crop yields and suggest

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methods to improve data collection and validation (Lobell and Burke, 2010; Lobell and Gourdji, 2012).

8.2. Data Interoperability

Another significant challenge is data interoperability, which involves the ability of different systems and software to access and process data in a mutually intelligible format. In agriculture, data is often collected using various devices and systems, leading to compatibility issues. Addressing these challenges requires standardization of data formats and protocols, which is crucial for integrating diverse data sources (Wolfert et al., 2017; Liakos et al., 2018; Kamilaris and Prenafeta-Boldu, 2018). Other studies explore these interoperability issues and recommend adopting universal standards for agricultural data to facilitate the effective use of ML (Janssen et al., 2017; Aydin and Aydin, 2020; Baldin et al., 2025).

8.3. Integration of IoT Devices

The future of ML in agriculture includes greater integration of Internet of Things (IoT) devices, which collect and transmit data from various points in the agricultural process. IoT devices can provide real-time data on soil moisture, weather conditions, crop health, and more, enhancing the precision and accuracy of ML models (Verdouw et al., 2016; Ray, 2017). Future research could focus on developing advanced IoT solutions that are cost-effective and easily deployable in diverse agricultural settings. Other studies discuss the potential of IoT in transforming agricultural practices through enhanced data collection and analysis (Kaloxylos et al., 2013; Aydin and Aydin, 2020).

8.4. Big Data Analytics

Alongside IoT, big data analytics will play a crucial role in the future of agricultural ML. Managing and analyzing vast amounts of data generated from multiple sources can uncover insights that would be impossible to detect by human analysis alone (Wolfert et al., 2017; Kamilaris et al., 2017). Future trends should aim at improving big data infrastructure and analytics tools to handle the complexity and volume of agricultural data effectively. Zhang et al. (2020) emphasize the need for sophisticated big data systems that can integrate and analyze data from various sources to improve decision-making in agriculture.

8.5. Ethical Considerations

As ML technologies advance, ethical considerations must be addressed, particularly regarding data privacy and the potential displacement of workers. Ensuring that data used in ML applications is collected and processed ethically is paramount (Hanna et al., 2025; Fletcher, 2021). Moreover, there is a need to consider the social implications of automating tasks traditionally performed by humans. Other studies discuss these ethical challenges and suggest frameworks for addressing them in the development of agricultural technologies (Cardoso and James, 2012; Preston and Wickson, 2016).

8.6. Sustainable Practices

The integration of ML in agriculture must also focus on promoting sustainable practices. ML can help optimize the use of resources such as water and fertilizers, reduce the environmental footprint of farming, and support sustainable crop and livestock management practices (Tullo et al., 2019; Monteiro et al., 2021; Tilman et al., 2002). Future research should aim at enhancing ML applications that contribute to sustainability goals. Other studies highlight the role of advanced technologies in achieving sustainable agriculture, emphasizing the importance of environmentally friendly practices (Foley et al., 2011; Das et al., 2023; Donmez et al., 2024).

8.7. Climate Adaptation

Looking ahead, ML models need to be further developed to help agriculture adapt to climate change. Predictive models that can forecast long-term climate impacts on agricultural productivity are essential (Moore and Lobell, 2015; Hansen, 2002). This includes developing ML applications that can suggest adaptive measures for extreme weather events, changing precipitation patterns, and shifting temperatures. Brown and Funk (2008) explore how ML can be used to model climate adaptation strategies, emphasizing the need for models that can predict and mitigate the impacts of climate variability.

8.8. Automation and Robotics

The future of ML in agriculture also lies in the advancement of automation and robotics. Autonomous tractors, drones, and robotic harvesters equipped with ML algorithms can perform tasks more efficiently and with less human input, increasing productivity and reducing labor costs (Bac et al., 2014; Perez-Ruiz et al., 2014; Saleem et al., 2021; Ghobadpour et al., 2022). Research in this area could focus on improving the intelligence and autonomy of agricultural robots. Other studies discussed the integration of ML with agricultural robotics, highlighting the potential for enhanced efficiency and productivity (Saleem et al. 2021; Araujo et al., 2023).

8.9. Addressing Implementation Challenges

Finally, addressing the practical challenges of implementing ML in agriculture, such as high costs, lack of technical expertise, and resistance to technological change, is crucial (Rotz et al., 2019; Van der Burg et al., 2021). Future directions should include developing cost-effective ML solutions and training programs for farmers to increase technology adoption. Schimmelpfennig (2016) addresses these implementation challenges and suggests economic strategies to enhance the adoption of technological innovations in agriculture.

In conclusion, while the challenges facing the adoption of ML in agriculture are significant, the potential benefits and advancements in the field are immense. Addressing these challenges through continued research, ethical considerations, and a focus on sustainability will pave the way for more innovative, efficient, and sustainable agricultural practices.

8.10. Governance and Ethical Oversight in Agricultural AI

The increasing integration of AI and ML in agriculture necessitates active government involvement in setting ethical, legal, and operational standards. Governments play a crucial role in regulating data ownership, ensuring fair access to AI technologies, and protecting smallholder farmers from digital exclusion (Jouanjean et al., 2020). Public policies are also essential for promoting transparency and accountability in AI-driven decision-making, particularly in areas such as automated resource allocation, crop insurance, and subsidy distribution (Carolan, 2020). Moreover, government-supported training programs and subsidies can facilitate the adoption of smart farming tools in under-resourced regions, closing the digital divide and ensuring equitable access to technological advancements.

Beyond labor displacement, AI in agriculture also poses risks such as algorithmic bias, over-reliance on predictive models, and environmental over-optimization. For instance, biased or poorly trained models could misrepresent pest threats or irrigation needs, leading to crop failure or resource waste (Tzachor et al., 2022). Additionally, opaque decision-making systems may reduce farmer agency, creating dependency on AI tools without a clear understanding of their limitations (Ryan and Stahl, 2021). Governments and regulatory bodies must therefore develop robust AI governance frameworks that include auditing, ethical standards, and stakeholder involvement, to prevent harm and foster trust in AI-driven agricultural innovations.

9. Conclusion

In concluding this comprehensive review of ML applications in agriculture, it is evident that ML has substantially enhanced agricultural productivity and sustainability. From precision agriculture and crop management to livestock farming and climate adaptation strategies, ML has proven instrumental in transforming traditional farming methods (Wolfert et al., 2017; Liakos et al., 2018). The use of predictive modeling for crop yield, disease detection, and resource optimization has enabled more precise and efficient farming practices, leading to increased outputs and reduced waste. Likewise, in livestock management, ML technologies have facilitated improved health monitoring and breeding practices, which have not only boosted productivity but also enhanced animal welfare (Monteiro et al., 2021). These advancements underscore the significant impact of ML on the agricultural sector, highlighting its potential to address both current challenges and future demands.

The progression of ML technologies in agriculture continues to evolve rapidly, driven by innovations in data collection, analysis, and automation. The integration of IoT devices and big data analytics has provided a wealth of precise, real-time data, allowing for more accurate and dynamic decision-making processes (Ray, 2017; Zhang et al., 2020). As these technologies mature, they promise even greater efficiencies and capabilities, potentially revolutionizing the agricultural landscape. Moreover, the continued development of ML models tailored to specific agricultural needs—such as climate-resilient farming practices and sustainable resource management—reflects a growing recognition of the need to adapt to global changes and pressures (Moore and Lobell, 2015; Brown and Funk, 2008). However, the expansion of ML in agriculture also necessitates careful consideration of ethical and sustainability issues. As we move forward, it will be crucial to balance technological advancements with the needs and well-being of both local farming communities and the broader ecosystem. Ensuring the equitable distribution of technology benefits, protecting data privacy, and promoting sustainable practices are essential steps in achieving this balance (Schimmelpfennig, 2016).

In summary, the future of agriculture is inextricably linked to the advancement of ML technologies. Continued research and development in this area are vital for realizing the full potential of ML in enhancing agricultural productivity and sustainability. By addressing the challenges and harnessing the opportunities presented by ML, the agricultural sector can continue to innovate and adapt, ensuring food security and environmental sustainability for future generations. This journey, while complex, is ripe with opportunities for significant impact, promising a smarter, more efficient, and sustainable agricultural future.

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