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Smart Agriculture: IoT and Machine Learning for Crop Monitoring and Precision Farming

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Abstract: Through the implementation of cutting-edge technology like the Internet of Things (IoT) and machine learning, smart agriculture, which is also referred to as precision agriculture, is bringing about a revolution in the conventional agricultural techniques that have been used for generations. The purpose of this article is to present an overview of how the Internet of Things (IoT) and machine learning are utilised in crop monitoring and precision farming in order to improve production, maximise resource usage, and reduce environmental consequences. The Internet of Things (IoT) devices that are connected with sensors are placed throughout agricultural fields in order to collect real-time data on a variety of environmental characteristics. These parameters include soil moisture, temperature, humidity, and nutrient levels. These sensors are connected to one another over wireless networks, which enables the transmission of data to centralised cloud-based platforms for statistical analysis in a smooth manner. In order to recognise patterns, correlations, and anomalies in the data that has been collected, machine learning algorithms are applied to the subject matter. The development of predictive models allows for the forecasting of agricultural yields, outbreaks of pests and diseases, and the implementation of ideal irrigation schedules. In order to enable farmers to make educated decisions about irrigation, fertilisation, pesticide application, and crop management methods, decision support systems offer them with recommendations and alerts that may be put into action. The report also discusses the Internet of Things (IoT) and machine learning for crop monitoring. In addition to that, challenges associated with precision farming are discussed in this research.

Keywords: *Smart Agriculture, IoT, Machine learning, Crop monitoring, precision farming*

1. Introduction

Agriculture is at a crossroads, necessitating innovation to secure sustainability and efficiency in the face of rising global population, changing climate, and limited resources. With the help of machine learning and the Internet of Things (IoT), smart agriculture is rising to the top as a promising new paradigm for precision farming and crop monitoring [1-2]. The importance and pressing necessity of smart agriculture in contemporary farming techniques are explored in this introductory piece. Improving agricultural production is crucial since the demand for food is rising rapidly as a result of both population expansion and shifting eating habits. Nevertheless, traditional agricultural practises frequently fail to maximise the use of resources, resulting in inefficiency, loss, and harm to the environment [3-6]. With the help of the Internet of Things (IoT) and machine learning, "smart agriculture" is reshaping farming in this way. Precise control of agricultural inputs like water, fertilisers, and pesticides to optimise yields while reducing resource consumption and environmental effect is at the core of smart agriculture. Deploying sensors that are Internet of Things (IoT) enabled in the field gives farmers access to data on soil conditions, weather patterns, and crop health in real-time, giving them unparalleled insights into their operations. Farmers are able to customise their interventions to meet the unique demands of each crop and field thanks to this data-driven approach, which enables precision decision-making [7–12]. The massive volumes of data produced by Internet of Things (IoT) sensors can only be meaningfully analysed with the help of machine learning algorithms.

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Fig 1. Precision Farming and Crop management [13]

Machine learning algorithms are able to optimise agricultural techniques, forecast crop yields, and spot outliers by examining past data and finding trends. Also, these algorithms are always getting better at what they do because they learn and adapt. Beyond improving output, smart agriculture is important because it solves sustainability problems in agriculture [13]. Droughts, pests, and illnesses are becoming more common as a result of climate change, so farmers must find ways to adapt quickly. Farmers can react quickly to changing environmental circumstances and reduce risks using smart agriculture's adaptive management practises. Smart agriculture also has the potential to help farmers, especially smallholders in poor nations, make a living. Smart agriculture helps farmers improve their income and economic resilience by giving them access to real-time data, market insights, and precision tools. This allows them to raise their yields, decrease post-harvest losses, and reach higher-value markets. There is no denying the importance and necessity of smart agriculture given the increasing number of issues that the agricultural sector is facing. Smart agriculture provides a way forward for resilient food production systems that can fulfil the demands of both current and future generations by utilising the power of machine learning and the Internet of Things.

2. Existing research

The evolution of precision agriculture has been marked by significant advancements in technology, data analytics, and agricultural practices over the past few decades. Here's an overview of the key stages in the evolution of precision agriculture:

1. Early Adoption of GPS Technology (1980s-1990s): The use of Global Positioning System (GPS) technology revolutionized precision agriculture by enabling accurate mapping and geolocation of field boundaries, soil samples, and agricultural inputs. Farmers began using GPS-guided tractors and equipment for precise navigation, seeding, and spraying, reducing overlaps and optimizing field operations.

2. Introduction of Remote Sensing and GIS (1990s-2000s): Remote sensing technologies, such as satellite imagery and aerial photography, became increasingly accessible for monitoring crop health, soil moisture, and vegetation indices.

3. Emergence of Variable Rate Technology (VRT) (2000s-2010s): Thanks to Variable Rate Technology (VRT), inputs like irrigation water, fertilisers, and pesticides might be precisely applied according to field-specific geographic variability. The use of sensor-based technologies, including crop sensors and soil moisture probes, allowed for the adaptive control of agricultural inputs and real-time monitoring.

4. Integration of IoT and Data Analytics (2010s-present): The widespread availability of sensors and devices connected to the Internet of Things (IoT) has made it possible to track the status of crops, machinery, and the surrounding environment in real time. An expanding number of data analytics systems and machine learning algorithms are being used to sift through mountains of data in search of useful insights that may be used to improve farming techniques. To facilitate data-driven decision-making, predictive analytics, and autonomous operations in agriculture, smart agriculture solutions utilise the Internet of Things (IoT), machine learning, and cloud computing.

5. Sustainability and Environmental Stewardship (now and in the future): As precision agriculture develops, there will be an increased focus on these three concepts. In order to reduce resource consumption, lessen the effects of climate change, and improve ecosystem services, precision farming techniques are using technologies including integrated pest control, cover cropping, conservation tillage, and precision irrigation.

Precision agriculture has progressed thanks to new technologies, insights derived from data, and an increasing awareness of the need of environmentally friendly and economically viable agricultural methods. Precision agriculture is going to be an important part of the future of agriculture in terms of both feeding the world's expanding population and preserving its natural resources for the next generation.

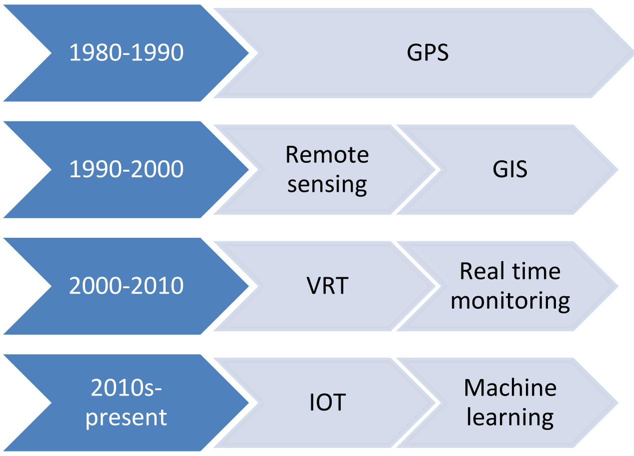

Fig 2. Historical Evolution

An investigation on the use of automated vision for the diagnosis Aduwo (2010) conducted research on cassava mosaic disease [1]. Global trends in agricultural applications were described by Barbosa (2020) [2]. Colace, F. (2018) recorded conversations that took place on farms [3]. Danso-Abbeam (2018) investigated agricultural extension and its effects on higher farm income and output. The northern part of Ghana was the site of the research [4]. Studies were carried out by Devlin, J. (2018) [5] on BERT, which stands for pre-training of deep bidirectional transformers for language comprehension. In 2020, a study proposal about E-AGRO was filed by J. Ekanayake. An intelligent chatbot is what I'm talking about. Using his expertise in AI and the internet of things, Auhor conducted this study to help the agriculture industry [6]. In 2018, M. Jain proposed the concept of FarmChat. The goal of this endeavour was to create a conversational agent that could answer farmers' inquiries [7]. N. Jain proposed Agribot in 2019. A research-based question-and-answer system specific to the agricultural sector was addressed [8]. In Kakani, V. (2020) [9], the author discusses how computer vision and artificial intelligence are being used in the food industry. Kapočiūtė-

Dzikienė introduced the domain-specific generative chatbot in 2020 [10] using a little quantity of data for learning. A knowledge-grounded chatbot with efficient attention mechanisms and built on dual Wasserstein generative adversarial networks was the subject of the study by Kim, S. (2020) [11]. For precise and early detection, this study proposed a new method: the hybrid deep learning model.

3. Problem statement

While Smart Agriculture, integrating IoT and Machine Learning for crop monitoring and precision farming, promises transformative benefits, it also presents several challenges and concerns that need to be addressed. This introduction highlights some of the key issues associated with the implementation of smart agriculture technologies.

One of the primary concerns revolves around the accessibility and affordability of these advanced technologies, particularly for smallholder farmers and those in developing regions. The initial investment required for deploying IoT sensors, data analytics platforms, and machine learning algorithms may pose significant barriers to adoption, limiting the potential benefits of smart agriculture to larger, more resource-rich farms.

Privacy and data security emerge as critical issues in the context of smart agriculture, where vast amounts of sensitive data are collected from farm operations. Farmers may be wary of sharing their data with third-party service providers or government agencies due to concerns about data ownership, misuse, and unauthorized access. Ensuring robust data protection measures and transparent data governance frameworks is essential to build trust and confidence among farmers.

Moreover, the complexity of integrating disparate technologies and data sources into seamless, interoperable systems poses significant technical challenges. Compatibility issues, data silos, and interoperability gaps may hinder the scalability and effectiveness of smart agriculture solutions, requiring standardization efforts and collaborative partnerships across the industry. Another pressing issue is the digital divide, which exacerbates disparities in access to technology and digital literacy among farmers. Bridging this divide requires targeted interventions to provide training, technical support, and infrastructure development tailored to the needs of smallholder farmers and rural communities, ensuring equitable access to smart agriculture solutions. Furthermore, there are concerns about the environmental impact of smart agriculture technologies, particularly regarding electronic waste and energy consumption. The proliferation of IoT devices and data centers may lead to increased energy consumption and carbon emissions, offsetting some of the sustainability benefits of precision farming practices. Sustainable design principles, energy-efficient technologies, and recycling initiatives are necessary to mitigate these environmental concerns. Finally, ethical considerations regarding the use of AI and machine learning algorithms in agriculture deserve careful attention. Biases in training data, algorithmic transparency, and unintended consequences of automated decision-making raise ethical dilemmas that must be addressed to ensure fairness, accountability, and social responsibility in smart agriculture applications. In conclusion, while smart agriculture holds great promise for enhancing productivity, sustainability, and resilience in the agricultural sector, it is essential to recognize and address the inherent challenges and issues associated with its implementation. By addressing these concerns through collaborative efforts and innovative solutions, smart agriculture can fulfill its potential as a driver of positive change in global food systems.

4. Need of research

The need to conduct research on crop monitoring using machine learning during precision farming is paramount for several reasons:

1. Optimizing Resource Efficiency: The use of machine learning algorithms allows for the exact management of agricultural inputs like water, fertilisers, and pesticides by analysing massive volumes of data acquired from sensors and remote sensing platforms. To assist farmers maximise resource use and avoid loss, research in this field can lead to the development of more accurate decision support systems and prediction models.
2. Enhancing Crop Yield and Quality: Researchers can find connections and trends in agricultural data that would not be obvious using standard approaches by applying machine learning techniques. Farmers may then use tailored interventions to enhance productivity and profitability based on these insights into the factors impacting crop growth, yield potential, and quality characteristics.
3. Improving Pest and Disease Management: Machine learning algorithms can analyze imagery data to detect early signs of pest infestations, diseases, and nutrient deficiencies in crops. Research in this area can lead to the development of automated monitoring systems and predictive models for timely intervention, reducing yield losses and the need for chemical inputs.

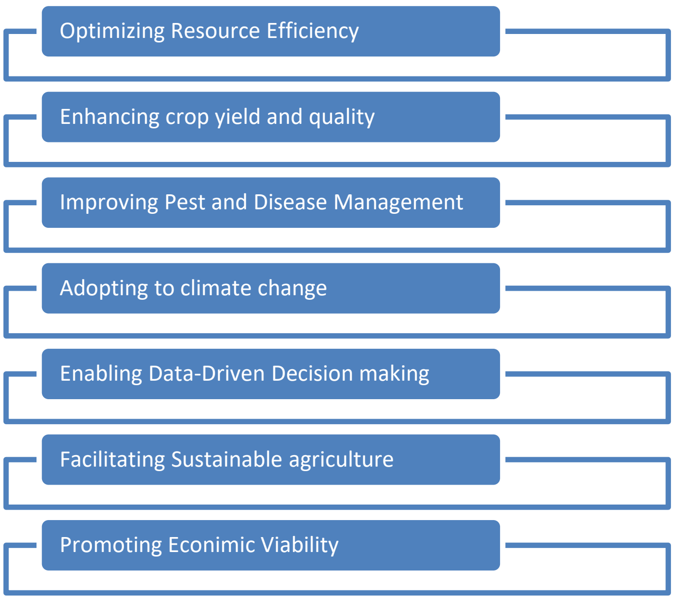

Fig 3 Reasons to perform crop monitoring using Machine learning

4. Adapting to Climate Change: "Climate change is expected to have significant impacts on agriculture, including changes in temperature, precipitation patterns, and the prevalence of extreme weather events. Research on crop monitoring using machine learning can help farmers adapt to these changes by providing insights into crop responses to environmental stressors and facilitating adaptive management strategies.
5. Enabling Data-Driven Decision-Making: In an era of data

abundance, research on crop monitoring using machine learning can help farmers make more informed decisions based on real-time data and predictive analytics. By integrating machine learning models into precision farming systems, researchers can empower farmers with actionable insights and recommendations for optimizing crop management practices.

6. Facilitating Sustainable Agriculture: Precision farming practices enabled by machine learning have the potential to promote sustainability by reducing the environmental footprint of agriculture. Research in this area can help identify sustainable farming practices, such as precision irrigation, cover cropping, and conservation tillage, that maximize resource efficiency while minimizing negative impacts on soil health, water quality, and biodiversity.

7. Promoting Economic Viability: Investing in research on crop monitoring using machine learning can lead to innovations that enhance the economic viability of farming operations. By improving crop yields, reducing input costs, and mitigating risks, precision farming technologies can contribute to the long-term profitability and resilience of agricultural enterprises.

Overall, conducting research on crop monitoring using machine learning during precision farming is essential for advancing agricultural sustainability, resilience, and productivity in the face of evolving challenges and opportunities". By harnessing the power of data-driven insights and innovative technologies, researchers can help shape the future of agriculture and ensure food security for generations to come.

5. Proposed work

Several critical processes, beginning with data collecting and ending with decision-making, comprise the process flow of precision farming's crop monitoring utilising machine learning. A general outline of the typical workflow is as follows:

1. Data Collection:

 - IoT Sensors: Place sensors all around the farmland to track things like soil moisture, temperature, humidity, nutrient levels, and even the weather.

 - Remote Sensing: Gain a better look at the crops and their surroundings with the use of satellite photography, drones, or drones outfitted with sensors.

 - Data Integration: Create a unified database or data lake by combining information from several sources, such as weather stations, historical records, Internet of Things (IoT) sensors, and remote sensing platforms.

2. Data Preprocessing:

 - Cleaning: Remove outliers, errors, and missing values from the collected data to ensure data quality and consistency.

 - Normalization: Scale the data to a standardized range to facilitate model training and improve convergence.

 - Feature Engineering: Extract relevant features from raw data, such as vegetation indices from remote sensing imagery or derived variables from sensor measurements.

3. Machine Learning Model Development:

 - Model Selection: "Based on the problem's nature, choose the suitable machine learning algorithms (e.g., regression for yield prediction, classification for disease detection).

 - Training: Train the ML model using either supervised or unsupervised learning by dividing the dataset into a training set and a validation set.

 - Hyperparameter Tuning: Optimize the model's performance and generalizability by fine-tuning its hyperparameters using methods like grid search or random search.

4. Model Evaluation:

 - Validation: Evaluate the trained model's performance on the validation dataset using appropriate metrics (e.g., accuracy, precision, recall, F1-score).

 - Cross-Validation: You may test the model's stability and ability to generalise to new data sets by running it through cross-validation.

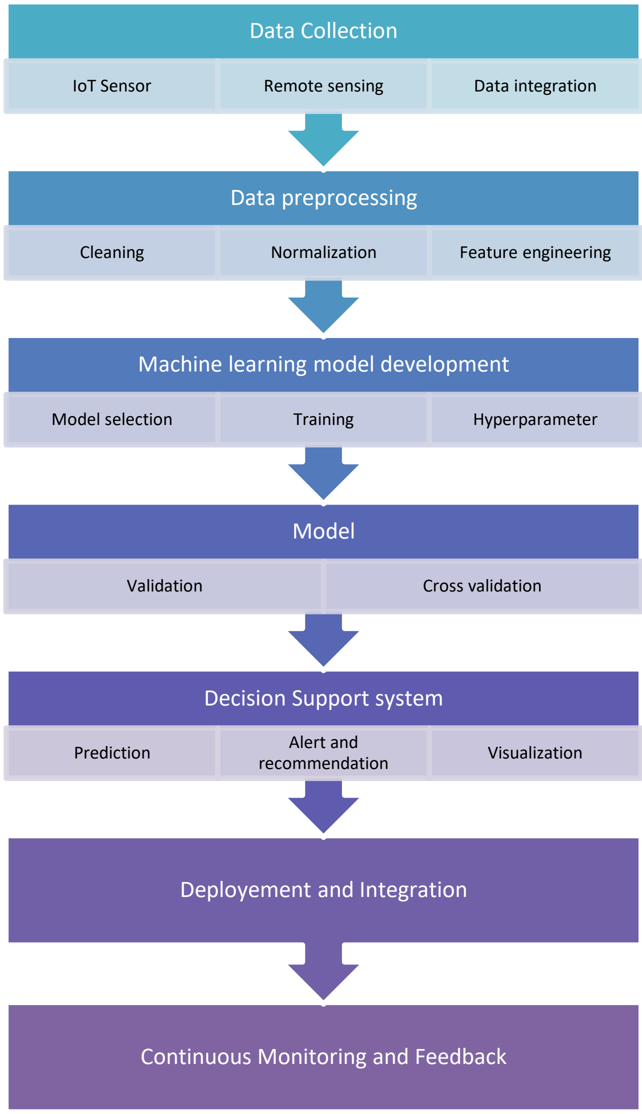

Fig 4. Model for crop monitoring

5. Decision Support System:

 - Prediction: Use the trained machine learning model to make predictions about crop yields, pest infestations, disease outbreaks, or optimal irrigation schedules.

 - Alerts and Recommendations: Generate alerts and actionable recommendations based on model predictions to guide farmers' decision-making processes.

 - Visualization: Visualize model outputs and insights through interactive dashboards or mobile applications to facilitate interpretation and decision-making.

6. Deployment and Integration:

 - Integration with Farm Management Systems: Integrate the machine learning-based crop monitoring system with existing farm management software and IoT platforms for seamless operation and data exchange.

- Deployment: Deploy the trained model and decision support system in the field, either locally on edge devices or in the cloud, depending on computational requirements and connectivity constraints.

7. Continuous Monitoring and Feedback:

- Data Update: Continuously collect new data from sensors and remote sensing platforms to update the model and adapt to changing environmental conditions.
- Model Retraining: To keep the machine learning model accurate and useful over time, retrain it periodically using updated data.
- Feedback Loop: Incorporate agronomic and farmer input to enhance model performance, fine-tune decision-making algorithms, and handle new problems or user demands.

Farmers and agricultural practitioners can leverage machine learning for precise crop monitoring and decision-making, leading to improved yields, resource efficiency, and sustainability in precision farming practices.

6. Simulation Results

Real-time datasets has been accomplished via the use of drones in agricultural areas. Following the conclusion of the training, a testing procedure was carried out in order to get the confusion matrix, which is shown in the part that follows.

6.1. Crop monitoring accuracy

Confusion matrix obtained in the case of conventional research is shown in Table 1.

Table 1. Previous work Confusion matrix

	Damaged Crop	Normal Crop
Damaged Crop	1974	24
Normal Crop	26	1976

Table 2 is presenting confusion matrix in case of proposed work.

Table 2. Proposed work Confusion matrix

	Damaged Crop	Normal Crop
Damaged Crop	1985	13
Normal Crop	15	1987

6.2. Comparison of Accuracy Parameter

Table 3 is showing the comparative analysis of accuracy parameters in case of conventional and proposed work.

Table 3. Accuracy in case of proposed model

Measure	Previous	Proposed
Accuracy	0.98	0.99
Precision	0.988	0.9935
Accuracy	0.9875	0.993
F1 Score	0.9875	0.993

Considering table 3, there is graphical representation of average accuracy parameters in the case of the proposed and previous model is shown in figure" 4.

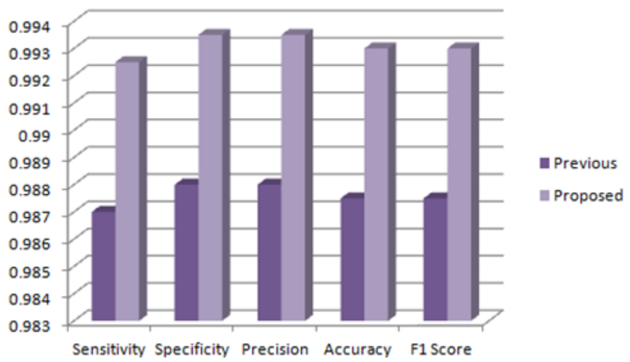

Fig. 5. Comparison of previous and proposed work considering accuracy parameters

Sensitivity and specificity of previous and proposed approach has been shown in table 4

Table 4. Comparison of sensitivity and specificity

Measure	Previous	Proposed
Sensitivity	0.987	0.9925
Specificity	0.988	0.9935

Considering table 4, there is graphical representation of sensitivity and specific for proposed and previous model is shown in figure 5.

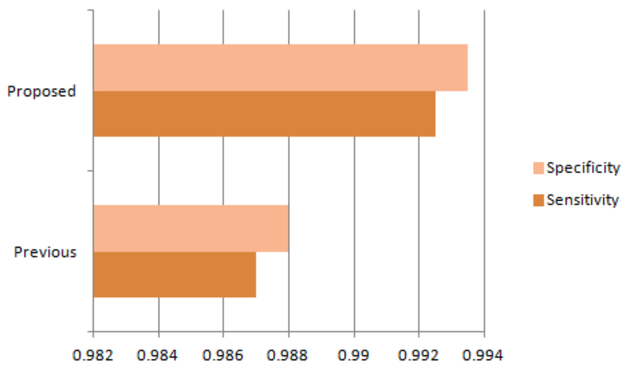

Fig. 6. Comparison of specificity and sensitivity of previous and proposed work

7. Conclusion

In conclusion, A new age of sustainability, efficiency, and production has dawned in agriculture with the integration of machine learning into precision farming for crop monitoring. The described process flow makes it clear that machine learning algorithms, when combined with Internet of Things (IoT) sensors and remote sensing technology, provide farmers with a potent toolbox for optimising crop management methods and making educated decisions.

Gaining insights into soil conditions, weather patterns, and crop health is made possible by utilising the quantity of data generated from fields. This data allows farmers to customise treatments to match the specific demands of their crops. With this data as their basis, machine learning models can optimise irrigation schedules, identify pests and illnesses, forecast crop yields with high accuracy, and offer timely suggestions to increase production while reducing resource waste.

The deployment of decision support systems based on machine learning further empowers farmers with actionable insights and real-time alerts, facilitating adaptive management strategies and ensuring proactive responses to emerging challenges. Additionally, the continuous monitoring and feedback loop inherent in precision farming practices enable ongoing refinement and improvement of machine learning models, enhancing their accuracy and relevance over time. However, while the potential of machine learning in precision farming is immense, several challenges remain, including issues related to data privacy, accessibility, interoperability, and environmental sustainability. Addressing these challenges requires collaborative efforts from stakeholders across the agricultural value chain, including policymakers, technology providers, researchers, and farmers themselves. In conclusion, The use of machine learning for crop monitoring in precision farming is an innovative strategy that has the potential to revolutionise the agricultural industry by bringing about more sustainable practises, higher yields, and less resource use. In order to guarantee food security for future generations while protecting the planet's natural resources, farmers must embrace innovation and harness the power of data-driven insights. This will help them negotiate the intricacies of contemporary agriculture.

8. Future Scope

The future scope for crop monitoring using machine learning during precision farming is promising, with several avenues for further research, development, and implementation. Here are some key areas of future exploration:

1. Advanced Sensing Technologies: Continued advancements in IoT sensors, remote sensing platforms, and imaging technologies will enable the collection of more granular and diverse data from agricultural fields. Integration of multispectral, hyperspectral, and LiDAR sensors can provide deeper insights into crop health, nutrient levels, and soil composition, facilitating more accurate and comprehensive monitoring.

2. Enhanced Data Analytics: Improving machine learning algorithms and prediction models to meet the unique requirements of precision agriculture is an area that will be the subject of future study. In complicated and ever-changing agricultural settings, crop monitoring systems could benefit from techniques like reinforcement learning, deep learning, and ensemble approaches.

3. Real-time Monitoring and Decision-making: By combining edge computing with real-time analytics, farmers will be able to keep a constant eye on their crops and react quickly to any changes. With the capacity to analyse data locally, edge devices with machine learning capabilities can improve scalability and reliability by lowering latency and dependency on centralised cloud infrastructure.

4. Autonomous Systems: The development of autonomous agricultural systems, such as robotic drones, unmanned ground vehicles, and intelligent machinery, will revolutionize crop monitoring and management. These systems can autonomously navigate fields, collect data, and perform targeted interventions, reducing the need for manual labor and improving efficiency and precision.

5. Integration with Precision Farming Technologies: Future crop monitoring systems will be seamlessly integrated with other precision farming technologies, such as precision irrigation, variable rate application, and robotic harvesting. This integration will enable holistic management of agricultural operations, optimizing resource usage and maximizing yield potential while minimizing environmental impact.

6. Data-driven Insights and Predictive Analytics: Technological progress in data analytics and AI will pave the way for more meaningful insights and practical suggestions to be gleaned from agricultural data. In order to help farmers make educated decisions and proactively manage risks, predictive analytics models can predict things like crop yields, insect outbreaks, and market trends.

7. Interoperability and Standardization: Efforts to establish interoperability standards and data exchange protocols will facilitate seamless integration of diverse data sources and technologies within the precision farming ecosystem. Standardized APIs and data formats will enable compatibility and interoperability across different platforms, devices, and software applications.

8. Sustainability and Environmental Stewardship: Future research will prioritize the development of sustainable farming practices that optimize productivity while minimizing environmental impact. Machine learning algorithms can help identify opportunities for resource efficiency, carbon sequestration, and biodiversity conservation, aligning agricultural production with broader sustainability goals.

In summary, The potential for precision farming to include machine learning into crop monitoring is marked by an ongoing commitment to innovation, cooperation, and optimization. In order to secure food security, environmental sustainability, and economic success for future generations, precision agriculture has the opportunity to revolutionise global food systems by utilising data-driven insights and cutting-edge technology.

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