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A Review on Smart Farming Agriculture Using Machine Learning Techniques

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Abstract

Agriculture is an important activity for food production, rural livelihoods and economic development. At the same time, farming systems face several pressures, including changing weather conditions, limited water resources, soil degradation, crop diseases, pests and the need to produce more food with fewer inputs. The growing global population, unpredictable climatic changes, and limited availability of natural resources pose significant challenges in meeting the increasing food demands of the present population. Machine learning (ML) offers methods for analysing agricultural data and supporting decisions about crop, soil and water. The review explains basic ML concepts and learning tasks before discussing applications such as crop-yield prediction, disease and weed detection, crop-quality assessment, animal monitoring, evapotranspiration estimation, soil-property prediction, remote sensing and smart farming. It also considers the growing connection between ML, the Internet of Things (IoT), unmanned aerial vehicles and geospatial data. The reviewed studies indicate increasing research interest in data-driven agriculture and the value of combining information from different sources. However, practical use is affected by data quality, local differences, infrastructure, model interpretation, computing requirements and the need for wider validation. The paper concludes that future work should focus on reliable, affordable and understandable systems that can be adapted to different farming conditions.

Keywords: Machine learning, Precision agriculture, Sustainable agriculture, Crop management, Yield prediction, Remote sensing, Internet of Things, Smart farming.

1. Introduction

Agriculture supports food supply, employment and economic activity in many parts of the world. Farming, however, is influenced by several changing factors. Crop growth depends on soil properties, rainfall, temperature, sunlight, water availability, nutrients, pests and diseases. These factors may vary from one field to another and may also change during a growing season. As a result, farmers need timely information to decide when to irrigate, how much fertilizer to apply, which areas require attention and when a crop may be ready for harvest.

Traditional agricultural decisions often depend on field observation, experience, laboratory testing and weather information. These methods remain important, but they may require considerable time and labour. Some field conditions are difficult to observe directly, and measurements collected at a few locations may not represent the full variation within a large field. Modern agriculture increasingly uses sensors, cameras, satellite images, unmanned aerial vehicles (UAVs), weather stations and farm machinery to collect larger amounts of information. These data sources create opportunities for computer-based analysis.

Machine learning is a branch of artificial intelligence that enables a computer system to identify patterns in data and use those patterns to make predictions or classifications. In agriculture, ML can analyse information about soil, crops, weather, animals and farm operations. For example, an ML model may estimate crop yield from weather and field information, classify a plant image as healthy or diseased, estimate soil moisture, or identify changes in animal

behaviour. The purpose is not simply to use advanced technology; it is to provide useful information that supports better agricultural decisions.

Leading technology companies such as Samsung, Apple, Google, and Microsoft are increasingly incorporating advanced technologies and intelligent systems into their products and services, highlighting the growing importance of technology in everyday life. Similarly, the application of Machine Learning (ML) in agriculture offers significant future potential for improving crop productivity, optimizing the use of water and fertilizers, predicting crop diseases, and supporting sustainable farming practices. The continued development and adoption of ML-based agricultural technologies can help farmers make better decisions, increase efficiency, reduce resource wastage, and contribute to a more sustainable and prosperous future for agriculture and society.

2. Fundamentals of Machine Learning

2.1 Meaning of machine learning

Machine learning is a method through which a computer system learns patterns from examples instead of depending only on fixed instructions written for every possible situation. A dataset contains examples, and each example is described by features. In agriculture, features may include rainfall, air temperature, soil moisture, soil nutrients, leaf colour, image measurements, crop variety or animal movement. The model uses the examples available during training to learn a relationship between the input information and the required output.

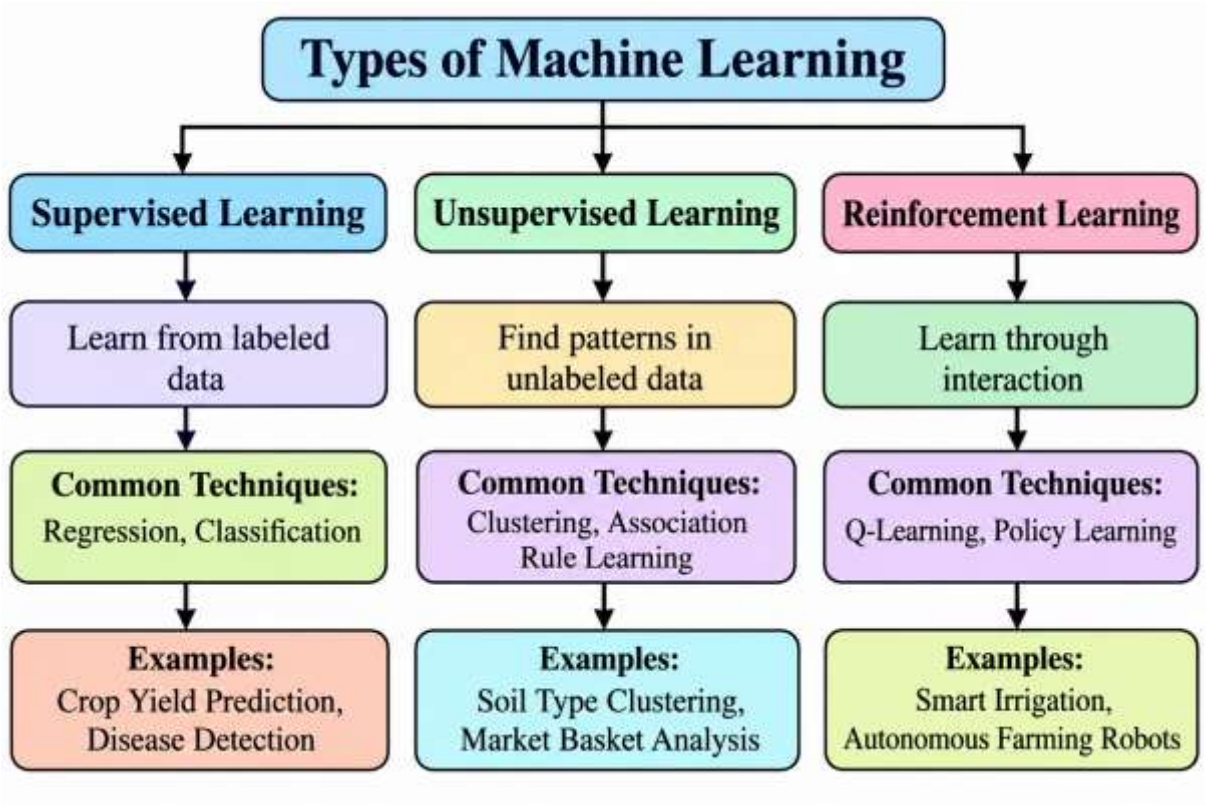
After training, the model can be applied to new data. Depending on the task, it may predict a numerical value, assign a category, group similar observations or reduce a large set of variables into a smaller representation. The quality of the result depends on the suitability of the algorithm, the amount and quality of the data, the way the model is trained and the method used to evaluate it.

2.2 Supervised learning

In supervised learning, the training data contain input examples together with the correct output for each example. The model learns to connect the input features with the known output. Classification and regression are common supervised learning tasks. Classification predicts a category, such as healthy or diseased plant, crop type or animal activity. Regression predicts a numerical value, such as crop yield, soil temperature, soil moisture or evapotranspiration.

2.3 Unsupervised learning

In unsupervised learning, the data do not contain a known output label for every example. The algorithm searches for structure or similarities within the data. Clustering is one example. In an agricultural setting, clustering may help group fields, soil samples or crop observations that show similar characteristics. Such groups may help researchers explore patterns, although an agricultural expert is often needed to interpret their practical meaning.



2.4 Training, testing and evaluation

A typical ML process begins with data collection, followed by data preparation and model training. The available data are commonly divided into training and testing sets. The training set is used to build the model, while the testing set is used to examine how well the model performs on examples it has not used during training. Evaluation measures depend on the task. The 2018 review lists measures such as mean absolute error (MAE), root mean squared error (RMSE), coefficient of determination (R^2), mean absolute percentage error (MAPE) and classification accuracy.

A good result on one dataset does not automatically mean that a model will work equally well in another region or season. Agricultural conditions vary with soil type, climate, crop variety, management practices and local geography. For this reason, testing under different conditions is important before a model is used to guide real farm decisions.

3. Common Machine Learning Models and Algorithms

The two review papers discuss several ML approaches. The 2018 review includes decision trees, support vector machines, artificial neural networks, instance-based methods, Bayesian models, ensemble learning and other algorithms. The 2025 review highlights decision trees, support vector machines, multilayer perceptron networks, Random Forest, XGBoost, convolutional neural networks and deep learning in more recent agricultural applications.

3.1 Decision trees

A decision tree makes predictions by dividing data into smaller groups through a sequence of decision rules. Each division is based on a feature, such as temperature, soil moisture or an image measurement. Decision trees can be useful when a researcher wants to understand the sequence of rules used to reach a prediction. Their performance depends on the data and the way the tree is developed.

3.2 Support vector machines

Support vector machines (SVMs) are used for classification and regression. They identify a boundary or function that separates data or predicts a value. The 2018 review describes SVM-based methods in crop disease detection, crop classification and soil-property estimation. The 2025 review also discusses SVMs as one of the methods used in precision agriculture.

3.3 Artificial neural networks

Artificial neural networks are computational models inspired in a general way by networks of connected processing units. They learn relationships from examples and can be used for classification or numerical prediction. The 2018 review reports neural-network applications in crop yield, disease detection, livestock behaviour, water-related estimation and soil analysis. A neural network may model complex relationships, but its training and interpretation can require care.

3.4 Random Forest and ensemble learning

Random Forest combines the predictions of multiple decision trees. Ensemble learning is a wider approach in which several models or learners are combined to produce a final result. The 2025 review describes Random Forest and XGBoost in crop and biomass prediction examples, including work using UAV-derived information. Combining models can improve prediction in some settings, but the benefit must be confirmed using suitable evaluation data.

3.5 Deep learning and convolutional neural networks

Deep learning uses neural networks with multiple processing layers. Convolutional neural networks (CNNs) are particularly useful for image-related tasks because they can learn visual features from image data. The reviewed literature describes their use in plant disease identification, crop and weed recognition, and image-based agricultural monitoring. These methods may require substantial training data and computing resources.

3.6 K-nearest neighbours and other approaches

K-nearest neighbours (KNN) makes a prediction by comparing a new example with similar examples in the training data. The 2018 review reports KNN in soil-drying assessment. Other approaches listed in the source include Bayesian methods, regression models, self-organising maps, extreme learning machines and dimensionality-reduction methods. The choice of an algorithm should be guided by the agricultural task, the available data and the need for reliable interpretation.

ML method	Main task described	Agricultural examples in the reviewed papers
Decision tree	Classification and regression	Crop classification and agricultural decision support
SVM / LS-SVM	Classification and regression	Disease detection, crop analysis and soil-property prediction
Artificial neural networks	Classification and regression	Yield, disease, animal behaviour, water and soil estimation
Random Forest / ensemble	Prediction and classification	Crop biomass, yield estimation and remote-sensing analysis
CNN / deep learning	Image analysis and classification	Plant disease, crop and weed recognition
KNN	Similarity-based prediction	Soil drying assessment

Table 1. Overview of Machine Learning Methods and Their Agricultural Applications

4. Machine Learning in Crop Management

Crop management was grouped into yield prediction, disease detection, weed detection, crop quality and species recognition. These tasks are closely connected with the need to monitor crop conditions and apply agricultural inputs at the correct place and time.

4.1 Crop-yield prediction

Crop yield is influenced by many factors, including crop variety, soil condition, rainfall, temperature, nutrient availability and management practices. Yield prediction attempts to estimate the amount of crop that may be harvested. Such estimates can support farm planning, storage, transport and decisions about the use of resources. The studies that used agricultural, meteorological, environmental, economic and harvest information. It also reports rice yield prediction using agricultural, weather and soil physical and chemical data, with support vector machines among the models considered.

The recent examples in which remote sensing and UAV data are combined with ML to estimate crop yield or biomass. It reports examples involving wheat and soybean. In one wheat-related example, Random Forest and XGBoost performed better than the other evaluated models in that study, and variables such as chlorophyll index and plant height were identified as important. In a soybean biomass example, combining spectral, textural and structural features from UAV images improved estimation. These findings show the value of combining several kinds of crop information, but the reported performance belongs to the individual studies and should not be generalised to every crop or region.

4.2 Plant disease detection

Plant diseases can reduce crop growth and yield. Early identification is important because it may allow farmers to take action before a disease spreads widely. ML systems that identify diseases in crops such as rice, wheat and other plants. Some studies used leaf images, while others used hyperspectral reflectance, fluorescence imaging or other sensor information. The models included neural networks, support vector machines and self-organising maps.

The reviewed examples include the detection of smut fungus in Silybum marianum, thrips in greenhouse strawberries, Bakanae disease in rice seedlings and yellow rust in wheat. Some systems aimed to identify infection before it could be easily seen by the human eye. The automated detection may be faster than visual examination in particular settings and can support more targeted use of fungicides or other treatments.

4.3 Weed detection

Weeds compete with crops for light, water, nutrients and space. Uniform herbicide application may treat areas where weeds are absent, increasing costs and environmental exposure. ML-based weed detection aims to recognise weeds and distinguish them from crops. The Such systems can support selective spraying, although reliable operation depends on image quality, field conditions and the ability to distinguish similar-looking plants.

5. Water Management and Irrigation

Water availability is essential for crop growth, but water resources are limited in many agricultural regions. Applying too much water can waste resources, while applying too little can affect crop development. ML can support water management by estimating variables such as evapotranspiration and by analysing weather and field information.

The studies that used artificial neural networks and other models to estimate daily, weekly or monthly evapotranspiration. The input information included maximum and minimum temperature, relative humidity, solar radiation, wind speed and sunshine duration. One study compared local station data with pooled data from multiple weather stations. Other examples estimated dew-point temperature using weather variables. These estimates can provide information relevant to irrigation planning.

The growing use of IoT devices and smart agricultural systems for monitoring soil conditions, weather and irrigation. Connected sensors can provide repeated measurements, while ML models can analyse the information and generate estimates or recommendations. This can support more timely irrigation decisions. However, the usefulness of such a system depends on sensor reliability, the representativeness of measurements and whether the recommendations fit the crop and local conditions.

6. Soil Management

Soil is a key part of agricultural production. Its physical and chemical properties influence water movement, nutrient availability, root development and crop growth. Soil measurements are often obtained through sampling and laboratory analysis.

ML applications for soil drying, soil organic carbon, moisture content, total nitrogen, soil temperature and soil moisture. For example, one study used precipitation and potential evapotranspiration data to evaluate soil drying for agricultural planning. Another study used visible-near infrared soil spectra from 140 samples to predict organic carbon, moisture content and total nitrogen. A further study used daily weather data to estimate soil temperature at several depths. Neural-network models were also used to estimate soil moisture from measurements related to forces acting on agricultural equipment.

Soil-related ML applications may support more informed nutrient and water management. However, the model must be tested with soil samples and conditions that represent the location where it will be used.

7. Precision Agriculture and Smart Farming

Precision agriculture aims to manage fields according to their actual conditions rather than treating every part of a field in exactly the same way. Soil, crop growth, water availability and pest pressure may vary across a field. A data-driven approach can use sensors, satellite images, UAVs and machinery records to identify these differences. ML can then help convert the collected information into maps, predictions or recommendations.

The precision agriculture seeks to improve productivity and profitability while reducing costs and environmental impact. One important idea is crop-specific or site-specific management, where inputs are adjusted according to field variability. ML can analyse geospatial data to support the allocation of fertilizers, water and other inputs. The use of ML in precision agriculture, particularly for targeted detection and management of crop stress, disease and weeds.

Smart farming refers to the use of connected technologies and data-based systems to monitor and manage agricultural operations. The review identifies smart farming as a growing research theme. It links smart farming with AI, IoT, deep learning, remote sensing and automated systems. These technologies can support real-time monitoring and more responsive management, but they also require suitable infrastructure, maintenance and technical knowledge.

8. Integration of IoT, Remote Sensing and UAVs

8.1 Internet of Things

The Internet of Things connects physical devices, such as sensors and equipment, so that they can collect and exchange information. In agriculture, IoT devices may monitor soil moisture, temperature, weather, crop conditions or irrigation equipment. IoT as an increasingly important theme in sustainable agriculture and gives examples of connected monitoring for soil conditions, weather, irrigation and pest control.

When IoT data are combined with ML, the system can move beyond data collection. The sensors provide observations, and the ML model analyses the observations to identify patterns or estimate future conditions. A connected system may then provide information to a farmer or, where appropriate, support automated control. The quality of the outcome depends on the quality and continuity of sensor data.

8.2 Remote sensing

Remote sensing collects information about land and crops without requiring direct contact with every part of a field. Satellite images and aerial sensors can provide information over large areas. The remote sensing as an important part of agricultural ML research, including crop-type mapping, crop-yield estimation and crop-condition assessment. Combining remote-sensing information with field observations can provide a broader view of agricultural conditions.

8.3 Unmanned aerial vehicles

Unmanned aerial vehicles, commonly called drones, can collect images and other measurements at relatively close range. UAVs equipped with multispectral or other sensors can capture differences in crop condition. The UAV-derived spectral, textural and structural features were used to estimate crop biomass or yield. It also discusses UAV-based prediction of crop nutritional information and crop monitoring. These examples show how aerial data can be combined with ML to support precision agriculture.

8.4 Combining multiple data sources

A major direction in recent research is the integration of information from different sources. For example, a crop-monitoring system may combine satellite images, UAV images, soil measurements, weather data and records of crop management. Each source provides a different view of the agricultural system. ML can help analyse the combined information, but differences in format, scale, timing and measurement quality can make integration difficult. The 2025 review identifies data integration as an important challenge and research need.

Data source	Examples of information	Potential agricultural use described in the reviews
Field and soil sensors	Moisture, temperature and other soil conditions	Soil monitoring and irrigation-related decisions
Weather stations	Temperature, humidity, wind, rainfall and solar radiation	Evapotranspiration and soil-temperature estimation
Satellite images	Large-area crop and land-surface observations	Crop-type mapping and yield-related analysis
UAVs and cameras	Spectral, visual, textural and structural crop features	Crop monitoring, disease identification and biomass estimation
Farm equipment	Machine and operational measurements	Monitoring field operations and supporting management
Animal sensors and cameras	Movement, chewing and activity patterns	Animal behaviour and welfare monitoring

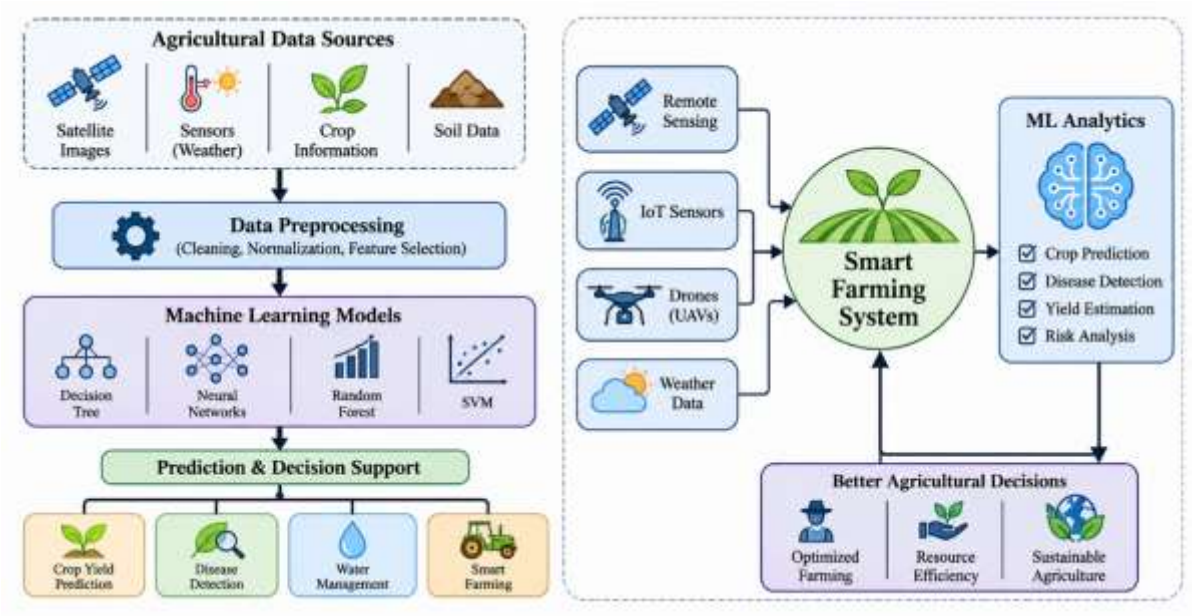
Table 2. Agricultural Data Sources and Their Uses

9. Research Trends in Machine Learning for Sustainable Agriculture

Their study used the PRISMA 2020 approach to organise the selection process and bibliometric indicators to examine publication quantity, citations and keyword use. The authors reported a notable increase in publications and identified 2024, 2022 and 2023 as the most productive years in the dataset.

The 2025 review describes a change in research themes over time. Earlier attention included weather data, while more recent work increasingly refers to artificial intelligence, IoT, remote sensing and smart farming. Deep learning, neural networks, data mining, crop management, crop disease detection, image processing and yield prediction also appear as important themes. These topics reflect a movement towards connected and data-rich agricultural systems.

The review provides a useful earlier point of comparison. It describes a broad set of applications, including crop, livestock, water and soil management, and identifies 40 articles in its selected review. Its examples show that ML was already being applied to field-level problems such as disease detection, crop classification, evapotranspiration and soil-property estimation. The review indicates that the research landscape has expanded and that newer technologies are increasingly being studied together.



10. Benefits and Practical Value

The reviewed papers indicate several possible benefits of ML in agriculture. First, ML can analyse many observations and identify patterns that may be difficult to recognise through manual inspection alone. Second, prediction models can provide estimates of crop yield, soil conditions, water-related variables or other agricultural measurements. Third, image-based methods can support crop, weed and disease recognition. Fourth, sensor-based monitoring can help farmers observe changes in crops, soil, weather or livestock.

A further benefit is the possibility of more targeted use of agricultural inputs. If a system identifies where a crop is stressed or where weeds are present, treatment may be directed to those locations rather than applied uniformly. Similarly, soil and weather estimates may support more informed irrigation and nutrient management. The 2025 review connects these uses with the aims of sustainable agriculture, including more efficient resource use and lower environmental impact.

ML can also support planning. Yield estimates may help with harvest preparation and resource allocation. Crop maps may help with land-use decisions. Animal activity monitoring may help farmers identify changes in behaviour. These applications do not remove the need for agricultural knowledge. Rather, they can provide additional information for farmers, researchers and agricultural professionals.

11. Challenges and Limitations

11.1 Data quality and availability

ML models depend on the data used to train and test them. If measurements are incomplete, inaccurate, inconsistent or unrepresentative, the model may produce unreliable results. Agricultural data may be collected using different sensors, equipment, sampling methods and recording formats. Missing observations and measurement errors can also affect model performance. The review identifies data management and data quality as important challenges.

11.2 Differences between regions and seasons

Agricultural conditions vary across geographical areas. Soil types, climate, crop varieties, irrigation practices and farm management differ from place to place. A model developed using data from one region may not work equally well in another region. The Seasonal variation can also affect crop images, weather patterns and disease occurrence. The 2 review identifies the need to adapt models to local conditions and to validate them in different agroecological settings.

11.3 Limited infrastructure and cost

Some agricultural ML systems depend on sensors, cameras, internet access, computing equipment and technical support. These resources may not be readily available to every farmer, particularly in areas with limited infrastructure or funding.

Devices also require installation, calibration, maintenance and replacement. A technically advanced model may have limited practical value if it is too expensive or difficult to operate in the intended farming environment.

11.4 Model interpretation and trust

Some ML models can produce accurate predictions but may be difficult for users to understand. Farmers and agricultural professionals need to know why a system gives a recommendation, especially when the decision effects crop health, costs or resource use. The review identifies model interpretability as an important issue. More understandable models and explanations of the factors influencing a prediction may improve confidence and responsible use.

11.5 Computing requirements

Deep learning and large-scale data analysis may require substantial computing power and storage. This can create difficulties where internet connectivity or computing facilities are limited. The review points to the need for lightweight and cost-effective models that can operate in resource-constrained environments. Such systems may be particularly important for small farms and locations with limited digital infrastructure.

11.6 Interoperability and integration

Agricultural information may come from devices and software that do not use the same formats or communication standards. Combining sensor readings, satellite data, UAV images, machinery records and farm-management information can therefore be difficult. The review identifies poor interoperability and the challenge of integrating multiple data sources as barriers to wider use.

11.7 Limited validation and long-term evidence

A model may perform well in a controlled experiment but still face difficulties when used over several seasons or in a different farming environment. The review highlights the need for more validation, scalability studies and longitudinal research. Long-term evaluation can help determine whether a system remains reliable as weather, crop conditions and management practices change.

11.8 Skills and Adoption

Successful use of digital agriculture requires more than developing a model. Farmers and agricultural workers may need training to operate devices, understand outputs and respond to recommendations. The review identifies limited digital literacy and training as barriers. Interdisciplinary cooperation between computer scientists, agronomists, engineers and farmers is also important because a model must address a real agricultural need.

12. Research Gaps and Future Directions

The reviewed papers suggest that ML has developed from individual prediction and classification tasks towards more connected agricultural systems. However, several research needs remain.

S. No.	Research Gap	Future Direction
1	Limited agricultural datasets	Develop diverse datasets covering different crops, soils and climates.
2	Limited geographical validation	Test models across different locations and growing seasons.
3	Data integration challenges	Integrate satellite, UAV, IoT sensor and weather data.

4	Lack of model interpretability	Develop explainable machine learning models.
5	High implementation costs	Design affordable and lightweight ML systems.
6	Limited automation	Integrate ML with IoT and automated farming equipment.
7	Lack of long-term evaluation	Evaluate sustainability, cost and practical performance.
8	Limited adaptability	Develop adaptive models for changing agricultural conditions.
9	Limited interdisciplinary research	Encourage collaboration among researchers, farmers and agricultural experts

Table 3. Research Gaps and Future Directions in Smart Agriculture

The reviewed studies indicate that machine learning has made significant progress in smart agriculture through crop prediction, disease identification, soil monitoring and yield estimation. However, several research gaps remain. The availability of diverse agricultural datasets, geographical validation and integration of multiple data sources are important challenges. Developing explainable and cost-effective machine learning models can improve reliability and make smart agricultural technologies more accessible to farmers. Furthermore, integrating machine learning with IoT devices, satellite imagery and automated equipment can support efficient agricultural monitoring and decision-making.

Another future direction is the development of adaptive systems. Agricultural conditions change over time, and a model may need to be updated when new data become available. Models that can respond to climate variability and changing field conditions may be more useful than systems that are trained once and then used without further evaluation. The reviewed sources support the need for adaptable and robust methods, although they do not establish one single method as best for all agricultural tasks.

13. Conclusion

Machine learning has become an important approach for analysing agricultural data and supporting decisions in crop, livestock, water and soil management. The review considered in this study show that ML has been applied to crop-yield prediction, disease and weed detection, crop-quality assessment, animal behaviour monitoring, evapotranspiration estimation and soil-property prediction. More recent research also gives increasing attention to remote sensing, UAVs, IoT, deep learning and smart farming.

The 2018 review by Liakos et al. provides detailed examples of agricultural applications and shows the variety of models used for different tasks. The 2025 review by Botero-Valencia et al. identifies strong growth in research publications and highlights the movement towards integrated and data-driven agricultural systems. Together, these shows the potential of ML to improve monitoring, prediction and resource management.

However, successful implementation depends on reliable data, local validation, suitable infrastructure, affordable technology and clear interpretation of model outputs. A model that performs well in one dataset or region may not provide the same results elsewhere.

Future research should therefore develop robust, explainable and resource-efficient systems and evaluate them under real farming conditions. Collaboration between computer science and agricultural experts will be essential. ML should be viewed as a decision-support tool that complements agricultural knowledge and helps farmers make informed choices.

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