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Artificial Intelligence in Agriculture: A Comprehensive Review of Machine Learning and Deep Learning Applications

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Abstract

The use of the artificial intelligence, especially in the fields of Machine Learning (ML) as well as Deep Learning (DL) is powerful in enhancing the benefits derived from precision agriculture, for instance, increasing crop yields, evaluating the health of plants, and managing resources. This review studies present literature from 2020 to 2024 and analyses the comparison of ML and DL models in detection of diseases, identification of pests, and water management. Our findings show that ML solution models such as Random Forests and SVM work better in small datasets while DL solution models like CNNs and YOLO v8 work better in big, complex, image-based tasks. But still, these fields are plagued by issues like data scarcities, the expense of computation, and lack of interpretability of the model. In this regard, we also examine how newly emerging technologies such as edge computing and explainable AI might overcome these challenges and justify AI as key technology in the advancement of agriculture in the future.

Keywords:factors analysis; facility layout; evaluation; selection;

1. Introduction

As the global population continues to rise, the demand for food production intensifies, placing increased pressure on the agricultural sector to produce more efficiently and sustainably. Traditional farming methods often struggle to keep pace with these demands without excessive resource use, prompting the need for innovative solutions like precision farming. This approach combines technology with data-driven insights, allowing farmers to make informed decisions about crop and soil management, water use, and pest control.

The introduction of artificial intelligence (AI), particularly through machine learning (ML) and deep learning (DL), has further enhanced precision farming's potential. AI-driven models can analyse vast amounts of data, uncovering patterns that inform crop yield predictions, resource allocation, and disease management strategies that were previously inaccessible. ML algorithms, for example, support real-time crop health assessments and optimized irrigation schedules, while DL techniques allow for early pest and disease detection via drone or satellite imagery.

This paper explores how AI, ML, and DL are revolutionizing precision farming, offering farmers tools to address major agricultural challenges with greater accuracy and sustainability. Through these technologies, the agricultural sector can better meet growing food demands while minimizing environmental impact and preserving resources.

1.1. Scope of the Review

This review examines recent studies on the application of machine learning (ML) and deep learning (DL) in precision agriculture, focusing on research conducted between 2020 and 2024. The analysis highlights the ways in which these technologies are employed across various farming activities, evaluating them based on key parameters such as retention levels, accuracy achieved, data volume and type required, and the operational scale. Additionally, this review identifies current limitations and barriers to the integration of ML and DL in agriculture, offering insights and recommendations for future advancements in this field.

2. Literature Review

2.1 Machine Learning Techniques in Precision Agriculture

Machine learning techniques like Decision Trees (DT), Random Forest (RF) and Support vector Machines (SVM) have been employed for numerous classification problems in the agriculture domain such as crop yield, disease, and pest identification. These techniques are effective when applied to structured data where the features have been apprehended and chosen rather than synthesizing the features.

- **Crop Yield Prediction Using Machine Learning**

  RF and SVM have been employed by a few researchers to forecast crop production with respect to environmental factors such as soil, weather condition, and satellite images [5]. The accuracy of these models may be good; however, they are mostly determined by the quality and quantity of the database.

- **Pest Detection Using Machine Learning**

  [2] evaluated the use of support vector machine (SVM) models combined with image processing techniques for real-time detection of paddy planthoppers. While the model

was effective in accurately identifying crop pests, challenges arose due to the substantial manual feature engineering required, given the high data volume involved.

2.2 Deep Learning Techniques in Precision Agriculture

Deep learning models are evidenced in the practice of image and sequence data applications in agriculture and long short-term memory networks (LSTM) as well as convolutional neural networks (CNN) have been on the rise. These models learn the attention-seeking features from the bulk of the data rather independently as compared to the former class of models.

- **Disease Detection Using Deep Learning**

  Where plant disease diagnosis has required some time, attention and effort, routines such as those in arms of CNN's have been accomplished kuerzdil and et al Faster RCCNN for plant diseases diagnosis. It is worth mentioning that these models are efficient even when applied to high-resolution images and have been used to detect crop diseases of cotton, grapes and paddy [3].

- **Water and Irrigation Management Using Deep Learning**

  Mitigation of water deficiency is undertaken also by manipulating irrigation practices through scheduling irrigation based on the prediction of soil moisture content. [6] explained how water requirements may be predicted in future depending past soil moisture content and weather data that may be intended to improve resources.

3. Comparative Analysis of ML and DL Models in Precision Agriculture

Below is a comparative analysis of the effectiveness of ML and DL models based on several key metrics:

Parameter	**Machine Learning (ML)**	**Deep Learning (DL)**
Accuracy	Moderate (70%-85%) on feature recognition because it depends on manual feature extraction.	High (85%-98%) when automatic feature learning is employed.
Data Requirements	Works fine with a smaller size of datasets (up to 1000 samples).	Larger sizes of the datasets are required (10, 000 + samples).
Scalability	Does not scale up easily; the process is time consuming	Scales up easily; applicable to big sized tasks.

	and tedious.	
Interpretability	More sensible with interpretable models to explain.	Black-box models; devoid of understanding.
Computational Cost	Low to medium edification.	High, especially for use in real-time situations.
Speed of Prediction	High, structured data has low latency.	Lower, because of the computational cost and large quantity of the models.
Example Applications	Detection of pests, prediction of yield.	Recognizing illnesses, monitoring through the use of drones.

4. Research Insights and Visual Comparisons

4.1 Figure 1: Application of AI in Precision Agriculture

Figure 1 explains the whole process involved in applying ML and DL models in precision agriculture where data is obtained using Uncrewed Aerial Vehicle (UAVs). The diagram also includes additional states such as Data Collection Techniques, AI Model Selection, Real-Time Monitoring, and Feedback Loops. This expanded workflow will also incorporate IoT integration, cloud processing, and recommendations to farmers.

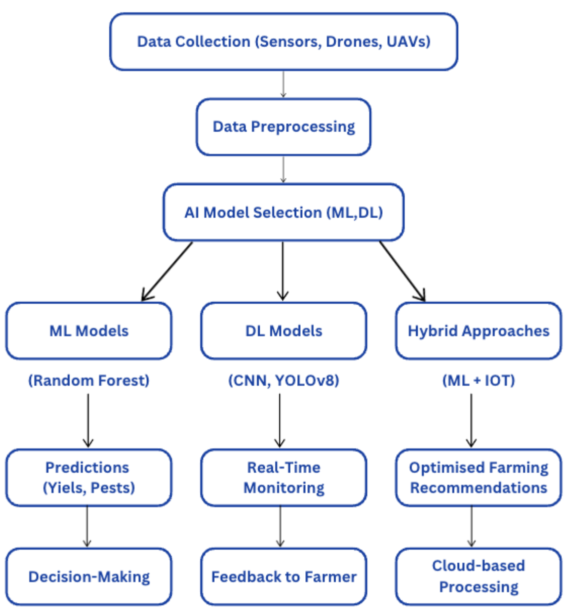

Figure 1: The procedural aspects of Machine Learning and Deep Learning Models in precision agriculture.

Each of the steps in Figure 1 is carefully illustrated in this section:

1. Data Collection (Sensors, Drones, UAVs)

- Explanation: The first stage involves collecting raw data from various resources such as sensors (Example: temperature, moistness), drones, uncrewed aerial vehicle (UAVs) etc. These devices harvest data from the fields regarding the status of crops, soil, climate, etc.
- Importance: ML and DL models cannot operate in the absence of high-quality data. Therefore, a model depends on all the correct information that is available

2. Data Preprocessing

- Explanation: Once the data has been gathered, it needs to be processed and usually cleaned and formatted so that it can be used in AI models. This stage covers the removal of noise, analysis of missing data and the conversion of raw data into organized one.
- Importance: Preprocessing makes certain that the data received is appropriate for the model hence increasing the accuracy and efficiency of the predictions made.

3. AI Model Selection (ML/DL based on Task)

- Explanation: To tackling this type of task, either ML or DL models are used. ML models such as Random Forest are better for structured data while DL models, in particular, CNN or YOLOv8, would be better for dealing with image and real time data.
- Importance: Correct model choice for a particular task allows achieving best results.

4. Model Categories:

- **ML Models (e.g., Random Forest)**
  Explanation: These models come in handy when features such as crops are to be analyzed for maize yield prediction for instance. They contain structured data where features are heavily extracted from human intervention.
- **DL Models (e.g., CNN, YOLOv8)**
  Explanation:Deep learning models are deployed when procuring complex information such as disease diagnosis via images or measuring level of pests in crops remotely. They learn features from information without assistance.
- **Hybrid Approaches (ML + IoT)**
  Explanation: A few studies such as vendor presented model which combines IoT with ML have addressed, these nets incorporate real time data obtained from sensors and actuators for more accurate agricultural techniques.

5. Predictions/Real-Time Monitoring/Optimized Recommendations

- ML Models: Provide forecasts of expected yields and the level of pest infestation by combining past and present information.
- DL Models: Heal the crops in a near remote way using sensors from the farmland to diagnose the crops, infective pests, and soil information to real-time data.
- Hybrid Approaches: Provide ways in which farming can be carried out efficiently e.g. watering/soil moisture and fertilizers application schedule based on integrated data from ML, DL, and IoT systems.

6. Decision-Making and Feedback

- Explanation: Following the completion of the models and conducting predictions or online supervising processes, the outcomes are utilized in the decision-making process. The scooping can be:
  - ML Models: Take active role to perform a task or change parameters (e.g., Change irrigation patterns, crop or apply pesticides).
  - DL Models: Automates the process and provides direct response to the farmer.
  - Hybrid Approaches: May use cloud processing for more complex decision making and data integration.

7. Cloud-Based Processing

- Explanation: When analyzing large datasets or making time-sensitive decisions, data processing and storage can be performed on distributed cloud-based systems to facilitate wide distribution and speed of computation as destined.

This workflow describes how precision agriculture employs the use of ML/DL technologies for on-the-spot decision-making enabling the farmers to make efficient and optimized farming activities based on scientific data.

4.2 Comparison of Approaches in Research Papers

This table provides a comparative overview of various machine learning approaches used in recent research papers to address different agricultural applications. Each study utilizes a specific model and technique, achieving varying accuracy levels on distinct data sizes. For example, [2] used SVM with image processing for pest detection, achieving 89% accuracy on 1,500 images, effectively identifying pests in rice fields. Similarly, [3] applied YOLOv8 for grape disease detection, reaching a high accuracy of 95% with 12,000 images. Other applications, such as soil moisture prediction with LSTM by [6], crop yield prediction with Random Forest, and crop species identification with CNN, show the diverse potential of machine learning in agricultural settings, enhancing strategies in pest control, irrigation, yield estimation, and species identification.

Table-1: Comparison of Approaches in Research Papers

Study	Model Used	Application	Accuracy	Data Size	Notable Results
[2]	SVM, Image Processing	Pest Detection (Planthopper)	89%	1,500 images	Effectively managed to find the pests in rice fields.
[6]	LSTM	Soil Moisture Prediction	91%	10,000 records	Improvised the water management and irrigation strategies.
[3]	YOLOv8	Disease Detection (Grapes)	95%	12,000 images	Efficiently detected leaf disease with high accuracy.
[5]	Random Forest	Yield Prediction	84%	800 samples	Crop yields were estimated basing on soil and climatic factors.
[1]	CNN	Crop Species Identification	92%	5,000 images	Analysed image and identified species and nutrient status.

4.3 Graph 1: Accuracy and Data Requirements of Different Models

The figure below compares the performance in terms of accuracy and the amount of data used in constructing the ML and DL models used in the selected research papers:

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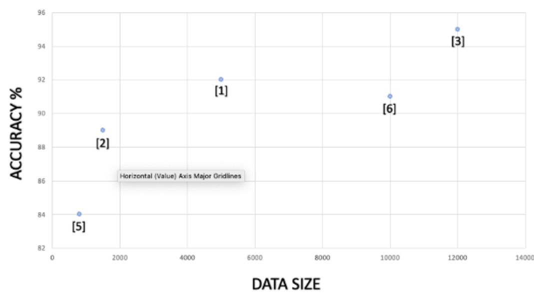

Graph 1: Accuracy and Data Requirements of Different Models

The graph evaluates the accuracy level and the level of data demanded by various Machine Learning (ML) and Deep Learning (DL) models in agricultural research and papers. Horizontal sono X-axis- Data size (small to the left and large to the right moving the towards the center) Vertical sono Y-axis- Accuracy (%) level expected.

Study	Model	Accuracy (%)	Data Size (samples)
[2]	SVM	89%	1,500 images
[6]	LSTM	91%	10,000 records
[3]	YOLOv8	95%	12,000 images
[5]	Random Forest	84%	800 samples
[1]	CNN	92%	5,000 images

Explanation of the Papers Used:

1. [2] – 1500 image dataset is provided for pest detection which employs a SVM technique. Accuracy of the model was 89% and works well with small dataset. Position on graph: (0.3, 0.89).
2. [6] – 10,000 records were dataset used and 91% accuracy achieved in soil moisture prediction using LSTM. Position on graph: (0.8, 0.91).
3. [3] –Deep Learning YOLOv8 model has been employed for disease detection with remarkable accuracy of 95% on 12000 image dataset. Position on graph: (0.85, 0.95).

4. [5] – Crop yield prediction was done with random forest technique using weaker dataset (800 samples) with 84% accuracy obtained. Position on graph: (0.2, 0.84).
5. [1] – A CNN was utilized in this study for crop species identification and was able to attain 92% accuracy with a moderate dataset size of 5,000 images. Position on graph: (0.6, 0.92).

X-Axis (Data Size) Scale:

The X-axis corresponds to data size, lying in a range of small datasets (around 500 samples) to large datasets (10,000+ samples). It can be normalized linearly with scaling from 0 to 1:

- Small datasets (0.1-0.4): ~500-2,000 samples.
- Moderate datasets (0.4-0.7): ~2,000-5,000 samples.
- Large datasets (0.7-1.0): >10,000 samples.

Y-Axis (Accuracy) Scale:

The y axis defines the model accuracy vis-a-vis estimates of 0.5 (50%) and 1 (100%).

- Lower accuracy (0.7-0.85): 70-85% accuracies mostly ML models.
- Higher accuracy (0.85-1.0): 85-100% accurate models are mostly DL models.

Visualization Tips:

- Make sure that SVM and Random Forest are associated with the lower half of the graph, rating moderate accuracy for smaller datasets.
- Make sure that YOLOv8, CNN and LSTM are placed at the top right for large datasets with higher accuracy.

5. Challenges and Limitations

5.1 Data Availability and Quality

The primary reason why agriculture in general is unable to benefit from the adoption of AI technologies is the absence of quality labelled datasets. The target of building data-driven DL models gets hindered due to unavailability of a large set of precisely annotated data.

5.2 Computational Complexity

Even though, the errors of such layers are small in the figure, also the computational requirements are quite high making adoption of such technologies by smaller agro-businesses difficult Conc CNNs LSTM, etc. are heavy computations and it is a challenge working on them for real-time operational purposes.

5.3 Interpretability Issues

People are not able to understand the way the models are working because the DL models are defined as black boxes which cannot be easily comprehended. Because of this, uptake of AI technologies is unlikely especially for sensitive areas in agriculture such as disease diagnosis [7].

6. Observations and Future Directions

6.1 The Role of Explainable AI

For AI models to be accepted and trusted by farmers, new means of explainable AI (XAI) will have to be provided. They would help shed light on the decision-making process of DL models and as a result, enhance the trust of users in the system.

6.2 Integration of Edge Computing

Edge computing could greatly enhance the effectiveness of real-time applications such as pest detection and monitoring of the crops using drones. It has been demonstrated that local data processing on drones or agricultural bots can help in obviating both latency and cloud processing costs (Farag, 2024).

6.3 Climate Resilient Agriculture

Traditional models will no longer be sufficient as climate prediction will become more difficult. Construction of agricultural models that will withstand up to climate change and predict extreme weather changes with measures that will mitigate the impact should be the target of subsequent studies.

7. Conclusion

Precision agriculture is now taking a new turn with the application of machine learning sand deep learning techniques improving monitoring of crops, diseases and resource usage. ML models are more convenient in terms of cost and processing challenges whereas DL is mostly useful for very thorough and high-level data like satellites and image data. That said, the broad penetration of AI to agriculture will be built on resolving data, compute and interpretability level constraints. However, integration with edge computing and air-drone architecture, and, development of AI models with climate resilience will usher the next disruption in agriculture.

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