Machine Learning Applications in Agriculture: Techniques, Challenges, and Future Perspectives

Mamta Devi[1], Sonu Chauhan[1*], Anushree[1] and Poonam Ranga[2]

[1]Department of Chemistry, [2]Department of Microbiology,
COBS&H, CCS Haryana Agricultural University, Hisar-125004, Haryana, India

Corresponding Author
Sonu Chauhan
Email: chauhansonu7777@gmail.com

OPEN ACCESS

Keywords

Agriculture, Future, Machine Learning

How to cite this article:

Devi, M., Chauhan, S., Anushree. and Ranga, P. 2026. Machine Learning Applications in Agriculture: Techniques, Challenges, and Future Perspectives. *Vigyan Varta* 7 (04): 255-259.

ABSTRACT

Agriculture plays a vital role in the economic growth of any country. With the increase of population, frequent changes in climatic conditions and limited resources, it becomes a challenging task to fulfil the food requirement of the present population. Precision agriculture also known as smart farming, has emerged as an innovative tool to address current challenges in agricultural sustainability. The mechanism that drives this cutting-edge technology is machine learning (ML). It gives the machine ability to learn without being explicitly programmed. ML together with IoT (Internet of Things) enabled farm machinery are key components of the next agriculture revolution. This article presents a comprehensive review of machine learning applications in agriculture, with a focus on soil property and weather prediction, crop yield forecasting, plant disease and pest detection, weed identification, and precision irrigation management. The adaptability and cost-effectiveness of ML make it a powerful tool for analyzing the complex input–output relationships of agricultural systems. Such systems exhibit non-linearity, temporal variability, and multiple unknown parameters, making machine learning approaches more suitable than traditional analytical methods. Overall, this review underscores the potential of ML to transform agriculture into a more efficient, resilient, and sustainable system and outlines future research directions for the successful integration of intelligent technologies in precision farming.

INTRODUCTION

The agricultural sector is a major contributor to the global economy ensuring food security. The growing demand for food due to the world's population expansion, climate change, pollution, groundwater and pump irrigation expenses, and freshwater scarcity are the major issues that modern agriculture is facing and traditional farming practices alone are no longer sufficient to meet these rising demands in a sustainable manner (Waqas *et al.*, 2025). Modern agricultural practices generate vast amounts of data through various sources, including field sensors, farming machinery, satellite imagery, drones, and weather monitoring systems. This data provides insights not only into farm operations (such as machinery performance and input usage) but also into dynamic environmental conditions involving crops, soil properties, and climate variability. Agritechnology and precision farming, commonly known as digital agriculture, are two new scientific fields that employ data-intensive techniques to boost agricultural output while minimizing negative environmental impacts. The integration of big data technologies and high-performance computing strengthened the application of ML in agriculture. Machine learning is a subset of Artificial intelligence (AI) that focuses on designing algorithms that automatically learn from data and make predictions or decisions without being explicitly programmed. It involves algorithms that can identify patterns in data and improve predictions over time as they are exposed to more information. In machine learning, a computer system is trained on a large amount of data and learns to recognize patterns and make predictions or decisions based on that data. The system can then use this knowledge to make predictions or decisions on new data that it has not seen before (Liakos *et al.*, 2018).

Applications:

1. **Soil Properties and Weather Prediction:** Prediction of soil properties is the first and most important step that affects crop selection, land preparation, seed selection, crop yield, and selection of manure and fertilizers. Soil properties are closely linked to the geographical and climatic conditions of the land and therefore play a vital role in agricultural decision-making. Soil property prediction primarily involves estimating soil nutrient levels, surface moisture content, and weather conditions throughout the crop growth cycle. However, human activities have substantially altered soil characteristics, thereby affecting soil quality and the accuracy of such predictions. A scientific analysis of soil nutrients, soil moisture, pH is important for determining the soil properties (Sharma *et al.*,2020). The soil nutrients are mostly monitored by electric and electromagnetic sensors. Acar *et al*. (2019) used Extreme Learning based Regression (ELM-R) model to predict soil surface humidity. The real time field data was extracted using polarimetric Radarsat-2 for a field located in Dicle university. The experimental results show the lowest Root mean square error (RMSE) of 2.19%

2. **Crop yield prediction:** Yield prediction is one of the most significant topics in precision agriculture and is of high importance to increase productivity. pH value, soil type and quality, weather pattern (temperature, rainfall, humidity, sunshine hours), fertilizers, and harvesting schedules are some of the parameters which pays a key role in predicting the crop yield. Kamir *et al*. (2020) used 9 ML algorithms RF, XG Boost, Cubist, Multi-Layer Perceptron (MLP), SVR, Gaussian Process, k-NN, and Multivariate Adaptive Regression Splines

and ensemble for yield prediction and results shows that SVR achieves the yield estimate with an R^2 of 0.77 and an RMSE value of 0.55 tha−1

3. **Disease detection:** One of the most significant concerns in agriculture is pest and disease control in open-air (arable farming) and greenhouse conditions. Plant diseases caused by fungi, bacteria, and other microorganisms derive nutrients from host plants, thereby adversely affecting crop growth and yield. If not identified and managed at an early stage, these diseases can lead to significant economic losses for farmers. To control such infections, farmers often rely heavily on pesticide application, which increases production costs. Moreover, the excessive use of pesticides poses serious environmental risks, including soil degradation and contamination of water resources, ultimately disrupting the ecological balance of agricultural systems. ML is an integrated part of precision agriculture management, where agro-chemicals input is targeted in terms of time and place. Ebrahimi *et al.* (2017) used morphological features and color indices of strawberry fruits to detect parasites (thrips). SVM model achieved 2.25% mean percentage error.

4. **Weed Detection:** Weed detection and management is a major challenge in modern agriculture, as weeds are widely recognized as a significant threat to crop productivity. Accurate identification of weeds is essential for sustainable farming however, distinguishing weeds from crops is often difficult due to their similar visual characteristics and growth patterns. In this context, machine learning (ML) techniques, combined with sensor-based technologies, offer an effective solution to detect weed accurately. These approaches enable cost-effective and environmentally friendly weed management by reducing reliance on chemical herbicides. Furthermore, ML-based systems can support the development of automated tools and robotic solutions for targeted weed removal, thereby enhancing efficiency while minimizing environmental impact.

5. **Drip irrigation:** Employing effective operational management of drip irrigation significantly reduces water consumption in crop production while enhancing crop yield. Due to increasing socio-economic and environmental demands, the adoption of drip irrigation has gained widespread recognition in agriculture, particularly for high-value crops such as fruits and vegetables. As compared to conventional irrigation methods, including sub-irrigation and sprinkler systems, drip irrigation offers several advantages efficient water utilization, the application of soluble fertilizers through fertigation, automation, reduced soil erosion, continuous field operations, decreased weed growth, and support for practices like double cropping.

Precision irrigation represents an advanced approach within smart farming, focusing on the efficient use of water to maximize crop productivity. It involves delivering the right amount of water at the right time and location within the field. This approach is often implemented through variable rate irrigation (VRI) techniques using drip or sprinkler systems. Recent advancements in field like on-farm sensor technologies, weather forecasting, IoT-based vegetation monitoring, and precision irrigation systems generate large amount of data. This data enables farmers to optimize water usage, improve crop yields, and enhance profitability. Furthermore, machine learning ML and DL techniques utilize historical and real-time data from sensors and IoT systems to support accurate predictions and informed decision-making in smart irrigation systems.

Challenges:

Machine learning has become increasingly important in agriculture, with the potential to improve crop yields, reduce costs, and optimize resource utilization. Another application of machine learning in agriculture is precision farming, which involves the use of sensors, drones, and other technologies to collect data about soil conditions, weather patterns, and plant health. Despite the significant potential of ML in transforming agricultural practices, several challenges hinder its widespread adoption and effective implementation that needs to be addressed. Some of the problems associated with ML in agriculture are-

- Agricultural lands are mostly situated in rural areas. Implementation of IoT architecture and WSN which requires cloud services for data storage and analysis is a big issue in rural areas where reliable internet connectivity is not available.
- One of the primary challenges of applying ML in agriculture is data collection and quality. Agricultural data is often heterogeneous, unstructured, and incomplete, making it challenging to gather and analyze. Furthermore, data quality can also be an issue as a high-quality data must be used while training a ML model.
- ML algorithms require large amounts of training data to learn patterns and make accurate predictions. However, there is often a lack of sufficient training data in agriculture, particularly for niche crops and farming practices.
- Implementing ML in agriculture can be expensive, and the return on investment may not be immediate or apparent. This can make it difficult for small farmers and agricultural communities to adopt ML technologies.
- Accurate prediction and classification through cognitive ability of machines is difficult in varying geographical conditions.
- Initial set up of digital farming which includes hardware and software requires huge investment.
- Deployment of smart sensors and other electronic gadgets requires heavy energy consumption.
- Bridging the gap between farmers and technology is a challenging task.
- Lack of ML algorithm knowledge among farmers.
- Due to lack of information and high costs of ICT implementation of sensors on farms become difficult.

CONCLUSION:

Precision agriculture is empowering the farmers with technology intended to get optimum outputs with precise inputs. IoT-enabled smart sensors, actuators, satellite images, robots, drones are some of the key technological revolutions that boosted the agriculture industry. These components play a vital role in collecting real-time data and accordingly making decisions without human support. Majority of farmers are non-experts in ML and, thus, they cannot fully comprehend the underlying patterns obtained by ML algorithms. For this reason, more user-friendly systems should be developed. Systems which are easy to understand and operate, would be valuable for example, a visualization tool with a user-friendly interface for the correct presentation and manipulation of data. In each phase of agriculture, starting from pre-harvesting to post-harvesting, researchers have applied ML algorithms to solve the complex problems. Today's need is to develop precise and customized machine learning models which can perform fast, automatically analyze bigger, more complex data and help to optimize the agriculture processes like classification, recommendations or predictions.

REFERENCES:

Acar, E., Ozerdem, M. S., & Ustundag, B. B. (2019). Machine learning based regression model for prediction of soil surface humidity over moderately vegetated fields. In *2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics)* (pp. 1-4). IEEE.

Ebrahimi, M. A., Khoshtaghaza, M. H., Minaei, S., & Jamshidi, B. (2017). Vision-based pest detection based on SVM classification method. *Computers and Electronics in Agriculture*, *137*, 52-58.

Kamir, E., Waldner, F., & Hochman, Z. (2020). Estimating wheat yields in Australia using climate records, satellite image time series and machine learning methods. *ISPRS Journal of Photogrammetry and Remote Sensing, 160*, 124-135.

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, *18*, 2674.

Sharma, A., Jain, A., Gupta, P., & Chowdary, V. (2020). Machine learning applications for precision agriculture: A comprehensive review. *IEEe Access*, *9*, 4843-4873.

Waqas, M., Naseem, A., Humphries, U. W., Hlaing, P. T., Dechpichai, P., & Wangwongchai, A. (2025). Applications of machine learning and deep learning in agriculture: A comprehensive review. *Green Technologies and Sustainability*, 100199.