



Advanced Machine Learning Techniques for Real-time Monitoring, Analysis and Optimization of Legume Crop Growth

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ABSTRACT

Background: This review study examines the transformative potential of machine learning (ML) methods for real-time and continuous evaluation of legume crop development. It provides a structured and comprehensive synthesis of current ML applications, highlighting their potential to improve legume crop management in terms of accuracy, efficiency, scalability and sustainability. Unlike existing reviews, this study specifically emphasizes real-time monitoring frameworks that integrate multi-source data (satellite, UAV, IoT and sensors) for legume crops.

Methods: Various machine learning methods, including supervised, unsupervised and deep learning paradigms, are reviewed with respect to their applications in crop health prediction, disease detection and yield estimation. The review further analyzes the integration of ML models with Internet of Things (IoT), edge computing and sensor-based systems to address challenges related to data quality, model interpretability, computational efficiency and real-time decision-making.

Result: While challenges remain, such as data heterogeneity, limited model generalization and the integration of ML with traditional agronomic practices, recent technological advancements demonstrate promising solutions. Key trends include the development of robust and transferable models, improved human-machine interfaces and decision-support tools for farmers. These advances have the potential to enhance precision, resilience and sustainability in legume crop monitoring, thereby contributing to global food security and climate-smart agriculture.

Key words: Disease detection, Internet of things, Legume crop management, Machine learning.

INTRODUCTION

The global agriculture sector is under increasing pressure to enhance productivity and sustainability in order to meet the nutritional demands of a rapidly growing population. Legumes, such as peas, beans and lentils, play a vital role due to their high nutritional value and their contribution to environmentally sustainable farming systems through biological nitrogen fixation. Accurate and real-time monitoring of legume crop development is therefore essential for maximizing yields, optimizing resource use and minimizing environmental impacts. However, traditional crop monitoring approaches are often labor-intensive, costly and prone to human error. Recent advances in machine learning (ML) provide new opportunities to develop intelligent, automated and continuous monitoring systems for legume production.

Legumes remain an essential component of daily diets, serving as a primary protein source for both humans and livestock. Legumes are the second most important agricultural plant family after the Poaceae (grass family), accounting for approximately 27% of global crop production. Economically significant legume species include soybeans, peanuts, chickpeas, lentils, beans, clover, alfalfa, lupins and carob, among others (Thudi *et al.*, 2021). Legumes are extensively cultivated in tropical and subtropical regions and contribute substantially to global food security. Their unique ability to fix atmospheric nitrogen through symbiotic relationships with soil microorganisms enhances soil fertility and reduces dependency on

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synthetic fertilizers. Consequently, legumes are widely incorporated into crop rotation systems to support sustainable agriculture and reduce production costs (Ma *et al.*, 2024; Koike *et al.*, 2023; Ghuriani *et al.*, 2023).

Machine learning (ML), driven by advances in big data analytics and high-performance computing, has emerged as a powerful tool for analyzing complex, data-intensive agricultural systems. According to Samuel (1959), ML enables machines to learn from data without explicit programming. ML techniques have been successfully applied across diverse domains, including bioinformatics (Kong *et al.*, 2007), biochemistry (Richardson *et al.*, 2016), medicine (Kang *et al.*, 2015; Zhang *et al.*, 2018), meteorology (Rhee and Im, 2017), economics, fisheries, finance, food security and climatology (Cho *et al.*, 2024; AlZubi, 2023; Wasik and Pattinson, 2024; Porwal, 2024). In

agriculture, ML models can process large volumes of heterogeneous data collected from IoT devices, remote sensing platforms and field sensors to support decision-making processes. Machine learning methods analyze historical and real-time data to predict crop growth, yield and quality, enabling data-driven management strategies (Shahrin *et al.*, 2020; Shaikh *et al.*, 2022). Agricultural ML models are commonly trained using weather conditions, soil characteristics, crop phenological stages and disease or pest incidence data.

The primary contribution of this review is a focused and critical synthesis of advanced ML techniques specifically applied to real-time legume crop monitoring. Unlike prior reviews that broadly address ML in agriculture, this study emphasizes (i) real-time data acquisition, (ii) integration of multi-platform sensing technologies and (iii) comparative analysis of ML paradigms for legume-specific applications. Furthermore, the review identifies current limitations, research gaps and future research directions to guide the development of scalable and practical ML-based solutions for precision legume farming.

Machine learning aims to improve task performance through experience derived from historical data. Within this data-centric paradigm, model performance generally improves as the volume and quality of training data increase, similar to how human expertise improves with experience (Vieira and Lopez, 2020). A key concept in ML is generalizability, which refers to a model's ability to produce accurate predictions on previously unseen data using patterns learned during training (Domingos, 2012).

Machine learning systems typically involve two main phases: training (learning) and testing (evaluation). Fig 1 illustrates the general architecture of a standard ML system. Pre-processing is a critical step that converts raw data into a usable format through data cleaning, integration of multi-source data and transformations such as normalization and categorization (Anagnostis *et al.*, 2020). Feature extraction and selection aim to identify the most informative attributes for model training (Zheng and Casari, 2018).

Feedback mechanisms are often employed to iteratively refine feature selection and pre-processing steps, thereby enhancing overall model performance.

During the testing phase, previously unseen data are introduced into the trained model to generate predictions, such as classification or regression outputs. Deep learning, a subset of machine learning, differs from traditional ML approaches by automatically learning hierarchical feature representations directly from raw data, eliminating the need for manual feature engineering (Kokkoti *et al.*, 2020). This capability makes deep learning particularly suitable for high-dimensional data such as images and sensor streams used in real-time crop monitoring.

MATERIALS AND METHODS

This review followed a structured literature review approach. A comprehensive literature search was conducted over a 10-year period (March 2014 to March 2024) using major scientific databases, including PubMed, Scopus and Web of Science. The search keywords included "Machine Learning," "Legume Crop Growth," "Real-Time Monitoring," "Remote Sensing," and "Yield Forecasting." Only peer-reviewed articles published in English that focused on ML-based applications for legume crop monitoring, management, or yield prediction were included. Review articles, conference papers and empirical studies were considered to ensure comprehensive coverage of methodological advances. Although this review does not strictly follow the PRISMA protocol, transparent selection criteria and screening procedures were applied to ensure relevance and quality. Future extensions of this work may incorporate a formal PRISMA-based systematic review framework.

RESULTS AND DISCUSSION

Implementation of ML in Real-Time Monitoring Systems

Several key components are required to successfully integrate machine learning techniques into real-time monitoring systems for legume crop growth. These

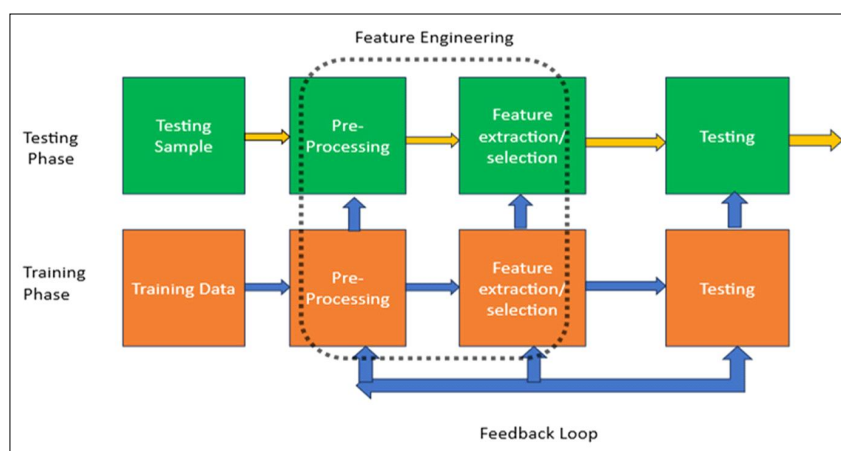


Fig 1: Graphical presentation of a common machine learning system.

components collectively enable continuous data acquisition, automated analysis and timely decision-making, which are critical for precision agriculture.

Satellite technology and imagery

Satellite imagery

High-resolution satellite imagery provides macro-scale and continuous information on crop health, growth patterns and environmental variability. Satellites equipped with multispectral and hyperspectral sensors collect data across multiple spectral bands, enabling the computation of vegetation indices such as the Normalized Difference Vegetation Index (NDVI), which is widely used to assess plant vigor and stress (Gumma *et al.*, 2019).

Satellite-based ML models support large-scale identification and monitoring of legume-growing areas, facilitating timely interventions such as irrigation scheduling, fertilizer optimization and early stress detection. Spectral indices derived from satellite images are often visualized using color composites, which can effectively highlight crop stress, nutrient deficiency and soil degradation. Compared to ground-based methods, satellite imagery offers broader spatial coverage but lower temporal resolution, making it particularly suitable for regional-scale monitoring.

Unmanned aerial vehicles (UAVs) and drone images

UAVs and drones equipped with high-resolution cameras and advanced sensors provide fine-scale, high-frequency observations that complement satellite data. Recent studies demonstrate that UAV-based imagery combined with ML algorithms significantly improves disease detection, growth stage assessment and nutrient stress identification. Unlike satellite platforms, UAVs allow flexible flight scheduling and ultra-high spatial resolution, enabling early detection of localized issues such as pest infestation or nutrient deficiencies. This early-warning capability supports precision input application and reduces unnecessary resource use, thereby improving yield and sustainability.

Ground-based sensors

Temperature and humidity sensors

Temperature and humidity sensors play a crucial role in monitoring environmental conditions that directly influence legume growth, flowering and pod development. Continuous measurement allows farmers to detect abiotic stress factors such as heat and excess moisture and implement timely mitigation strategies. When integrated with ML models, these sensors enable predictive analytics for stress management and disease risk assessment, enhancing crop resilience under changing climatic conditions (Kumari *et al.*, 2021).

Soil moisture sensors

Soil moisture is a critical determinant of legume productivity. Soil moisture sensors provide real-time information that

helps optimize irrigation practices and conserve water resources. ML-driven irrigation models trained on soil moisture data improve water-use efficiency and reduce risks of drought stress or over-irrigation, contributing to sustainable water management in legume cultivation (Durga *et al.*, 2018).

Nutrient sensors

Monitoring soil nutrient levels is essential for maintaining optimal legume growth and soil fertility. Nutrient sensors track macronutrients such as nitrogen, phosphorus and potassium, enabling site-specific nutrient management.

Continuous nutrient monitoring combined with ML-based recommendations supports precise fertilization strategies, reducing environmental impacts and enhancing crop yield. These technologies are particularly valuable in organic and sustainable legume production systems (Murray *et al.*, 2017).

Internet of things (IoT) devices

Automated irrigation methods

Automated irrigation systems leverage real-time sensor data and ML algorithms to optimize water application. Such systems dynamically adjust irrigation schedules based on soil moisture, weather forecasts and crop growth stage, reducing water waste and labor requirements while improving crop health (Kim and AlZubi, 2024).

Weather stations

IoT-enabled weather stations provide real-time data on temperature, rainfall, humidity, wind speed and solar radiation. ML models trained on weather data support predictive decision-making for irrigation, pest control and harvesting schedules, ultimately enhancing productivity and environmental sustainability (Alliance of Bioversity and CIAT, 2021).

Pest detection sensors

Pest detection sensors, including imaging devices and machine vision systems, enable early identification of pest and disease outbreaks. By integrating these sensors with ML classifiers, farmers can apply targeted treatments, reducing chemical usage and promoting environmentally responsible pest management (Urva, 2021).

External and historical data sources

External data

External datasets from agricultural institutions, meteorological agencies and government sources provide contextual information on soil types, climate patterns and regional productivity. Integrating external datasets with real-time monitoring improves model robustness and adaptability, enabling location-specific recommendations.

Historical crop data

Historical crop data provide insights into yield trends, disease outbreaks and management outcomes. When

combined with ML models, historical data enhance forecasting accuracy and support proactive decision-making, improving long-term legume productivity and resource efficiency.

Data preprocessing

Data cleaning

Handling missing values

It is an important stage in collecting information for proper evaluation and observation of legume crops. Missing information can be caused by a variety of factors, including failure of the device, communication mistakes and information gaps. Computation, calculation and the use of machine learning methods all help to close these spaces. For example, neighbouring values may be used to calculate missing soil moisture information for some time. The collected information may be strong and dependable, allowing for exact calculations and decision-making. Managing missing information correctly improves forecast and evaluation accuracy, resulting in improved legume crop management and income.

Noise reduction

It is important for successful management of information in legume-detecting systems. Environmental factors and device mistakes can cause noise to be introduced into information from devices. Noise is reduced by smoothing out separate systems, average movement and outlier identification. For example, applying a smoothing filter to soil moisture information capacity reduces unexpected changes that do not match facts. Effective noise reduction increases information quality, resulting in more correct views and better decisions in legume farming.

Standardization and normalization

They are important preprocessing phases for evaluating legume crop information. Standardisation is the process of correcting data to have a mean of 0 and a standard deviation of 1, meaning that data from various sources is similar. Normalisation corrects information to a confident range, usually between 0 and 1, making it easier to associate different information. These methods are important for the learning models to function successfully because they handle differences in units and scales. Standardisation and normalisation of data such as soil moisture points, nutritional value and growth rates results in regular, correct calculation and better decision-making for legume crop management.

Model training and validation

ML jobs are characterised as supervised or unsupervised based on the training signal produced by the learning classification. In supervised learning, the information is shared with input and output examples to develop an overall structure that relates input and output. In other conditions, inputs may be incomplete, with certain expected outputs missing or just providing a reaction to activities in an

atmosphere of change (reinforcement learning). The information gained (trained model) is utilised in supervised learning to predict the missing test data results (labels). Unsupervised instruction, on the other hand, fails to differentiate between training and test sets and fails to market the information. The beginner observes input data to discover unseen designs.

Supervised learning

Decision trees and random forests

Decision trees are popular due to their understanding and ability to handle a wide range of data types. Commonly used methods in this domain include the regression and classification tree, the chi-square method of the iterative dichotomiser and the automated interaction detector (Blockeel *et al.*, 2023; Wu *et al.*, 2022). Random forests are a team method that includes many decision trees to increase forecast correctness and prevent unnecessary fitting. Decision trees, for example, may label images of legume plants to identify disease presence and seriousness, whereas random forests can forecast the production of crops based on features such as soil moisture, temperature and NDVI.

Support vector machines (SVM)

Cervantes *et al.* (2020) created the SVM which is based on mathematical methods. It is used for resolving classification, regression and clustering problems. This method uses universal principles to achieve problem-solving in higher dimensions thereby allowing it to be applied across a wide range of situations. The most common use of SVM is support vector regression (Sharp, 2020), least-squares SVM (Zhang *et al.*, 2019), followed by forecasting algorithm-support vector machine (Soares and Anzanello, 2018). SVMs are good for high-dimensional environments where they are often used to quantify data about things. They use spectral fingerprints to identify different crops and provide insight into their health.

Neural networks

Convolutional neural networks CNNs are important for analyzing images and videos, processing pictures captured by drones or satellites that can detect patterns of disease development and nutrient stress in legume crops as well as monitor crop yield growth potentiality over time at any stage during plant growth cycle up until harvest date with some added advantage like possible identification of feral seedlings at an early stage while there is still time left before much damage becomes inevitable; Recurrent neural networks RNNs and long short-term memory LSTM networks help us study incoming device data over period of time so that we can predict future crop yields. In this case RNN solves this issue through a hidden layer where the hidden state plays a crucial role in maintaining continuity (Kousik *et al.*, 2021). Throughout calculating process the RNN has a memory which stores all the information collected within it.

Unsupervised learning

Clustering algorithms

Clustering methods are important for examining legume crop information because they group the same forms and discover different groups within the sample. Moisture levels in the soil, temperature and growth rate can be used by clustering methods to divide grounds based on similar climatic or crop conditions. This is useful for farmers to identify areas with comparable needs and adjust management plans such as adjusting irrigation plans or using precision farming methods. Such a method provides a valuable understanding of legume crop variability thus attractive general farming methods for increased profitability and long-term sustainability (Kartal *et al.*, 2020).

Principal component analysis (PCA)

PCA is a useful method for data reduction and pattern finding in legume crop data (Girgel, 2021). PCA minimizes redundancy by collapsing high-dimensional information into fewer dimensions while retaining as much variability as possible. The principal components analysis can reveal the important drivers of Crop growth and yields such as soil mineral levels, environmental conditions and crop health indicators. This allows farmers to concentrate on the main limiting factors of legume profit-making decisions about crop management. This enables farmers to understand better how different variables for various legume crops work thereby enhancing agricultural outcomes and efficiencies.

Reinforcement learning

It uses reasoning to make intelligent decisions based on specific requirements of leguminous plants aimed at increasing output while conserving resources through continuous problem-solving and learning.

Resource management

This technique Leverages fast information sharing in terms of resource utilization such as when to irrigate crops and apply manure. More output will come from RL models because they are active methods that learn through trial and error (RL Model); for example, it may optimize water usage by finding the best time to water based on moisture content in the soil as well as weather forecasts (Goodarzy *et al.*, 2020).

Autonomous farming systems

These approaches involving devices and machine learning can provide independent protection, watering and harvesting of legumes. Independent farming systems that pay close attention to weather conditions, soil moisture and plant health indices may improve resource supply inputs and outputs. These methods of legume cropping involve focused cultivation, water absorption as well and particular harvests leading to increased returns from crops and natural resources utilized in agriculture. The plan offers potential solutions for better farming practices that could lead to higher income generation as well as reduced environmental impacts on the development stages of a legume crop species. Table 1 gives an insight into machine learning techniques employed in addressing legumes.

Feedback and continuous improvement in machine learning for legume crop growth

Detailed data collection

Collecting information is important for examining and improving changes. Field-based and experimental tools collect data on several issues, including temperatures, soil humidity, level of nutrients and crop health symbols. These information sources provide a wide overview of the agricultural ecosystem and its current condition. The procedure gives a solid foundation for exact forecasting and rapid action through broad information collecting which involves all important components of legume crop development.

Feedback loop

This is important for testing and improving the learning of machine models used for observing crops. Once collected, the information is put into models for forecasting, which examine current and specified conditions. Any differences or changes are identified and this information is used to improve the models. This method shows that the models are always changing and improving. For example, if expected soil moisture levels often differ from real measurements, the model limits will be notified to help future forecasts connect experiential facts.

Promotion of sustainable farming practices

The changes improve ecologically friendly farming methods by increasing resource use. Forecast models, for example, may correctly determine groundwater levels,

Table 1: Comparing machine learning methods for legume crop management.

Technique	Description	Advantages	Challenges
Supervised learning	Uses labelled data to train prediction methods.	High accuracy	Requires labelled data
Unsupervised learning	Detects patterns in unlabelled data.	Can find hidden secrets.	Interpretability
Reinforcement learning	Optimal actions are learned via trial and error	Adaptable to changing environment.	Training complexity

allowing for better treatment plans and less water waste. Similarly, correct pest and disease forecasts help in the use of pesticides and limiting their effect on the environment. These methods lead to environmental preservation while also reducing farm functional costs, resulting in higher profits overall.

Iterative measurement and development

Repeated testing improves machine learning models over time. As more information is collected as time passes, the classification discovers new leanings and designs, allowing the models to develop. This method uses systems to increase their accuracy in imagining important variables including water needs, pest costs and nutrient problems. Regular model changes make sure that the system changes to changing climatic conditions and crop behaviours, resulting in improved accuracy in forecasting and features.

Challenges and limitations

The use of machine learning (ML) has a chance to improve the actual tracking of legume crop growth, several problems and restrictions prevent widespread acceptance and placement. These problems include quality of information and availability, modelling explanation, processing requirements, scalability and interaction with existing agricultural methods.

Data quality and availability

The use of artificial intelligence in legume observing crops is complex by data quality and availability issues. Accurate ML models require high-quality, complete datasets, yet inconsistencies, values that are missing and noise can all degrade their performance. Modern machines are required for significant data, that could be less available to all producers, particularly in nations with limited resources. Many data sources require thorough preparation for acceptable usage and quality.

Model concept

Modern machine learning systems, such as algorithms for supervised learning, have understanding limitations, sometimes behaving as “black boxes” with no visibility or trust in making choices. Farmers and agronomists might be unable to understand and trust the ideas. Basic models, such as regression using linear regression, are easy to understand but they may misunderstand the difficulty of crop development patterns. Managing the complexity of models and understanding is a major difficulty in agricultural machine-learning uses.

Computing resources

Models based on deep learning need wide information technology resources, particularly high-performance hardware such as GPUs, to train and continuous information analysis. This can be challenging for small-scale farmers and remote agricultural actions, as they may

lack the necessary infrastructure to support these computational demands.

Durability and generalization

Durability is also a significant concern. Models developed using data from certain locations or situations may not be applicable in other situations. Methods of farming and environmental factors vary significantly among areas; thus, systems must be able to manage this variation. Efficient ML systems that can be easily adapted to different situations are essential for widespread use. The result requires not just a large amount of data for training from multiple sources, but also new methods to ensure that the models apply successfully.

Integration with previous methods

Farmers' inability to ML methods in agriculture arises from an absence of faith, uniformity and a learning process. To gain acceptability, ML systems must be easy to use and offer obvious advantages. Communication between technology and farming professionals is essential for matching machine learning suggestions with current procedures and generating proven and practical solutions.

Data privacy and security

As information becomes more important in farm decision-making, challenges to the security and privacy of data arise. Farmers need to know that their data will be utilised properly and that private data will be preserved. Clear rules and strong security procedures are required to overcome these problems and develop confidence in ML applications.

Future prospects

Machine learning (ML) has an opportunity in the continuous monitoring of legume crop growth, due to many advances and novel developments. The Internet of Things, sensors and machine learning models can provide continuous, complete data on soil moisture, temperature and the health of plants, allowing for more accurate crop management through real-time analysis. Edge computing is expected to play a significant role in evaluating data closer to the source, decreasing delays, boosting data privacy and removing the demand for high-bandwidth connections. Creating cheap ML algorithms for devices at the edge will allow for real-time insights in remote places with limited connection. Future research will also focus on developing durable and generalizable machine learning models that can adjust to changing environmental circumstances and agricultural methods. Techniques such as learning transfer will be important in ensuring dependability over several conditions. Personalised agricultural solutions adapted to specific farm conditions will develop resource utilisation and maximise production, hence increasing total production. Furthermore, simple controls and instructional activities can promote adoption by providing farmers with clear, useful information and teaching them the information and abilities required to utilise modern technology. These

developments can change legume crop monitoring by improving utility, quality and durability in farming.

CONCLUSION

Machine learning used to evaluate legume crop development can change current farming. Machine learning is used to give correct, successful and flexible solutions for the health of crop testing, production forecasting and resource management. The present study focuses on the limits of the quality of system information, processing demands and the interaction of current methods. The addition of computers to the Internet of Things allows for continuous and fast data processing, even at a distance. The development of advanced, adaptable models, as well as personalised agricultural solutions designed for rare farm situations, will maximise resource utilisation and production. Creating instructional tools is essential for farmers to well apply ML methods and avoid wrong uses. These methods can likely improve the value, precision and duration of legume growth, increased food supply and a change in farming. The possible use of machine learning in farming is good and it will play a significant role in fulfilling the world's growing food needs.

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Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

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Data availability

The data analysed/generated in the present study will be made available from the corresponding authors upon reasonable request.

Availability of data and materials

Not applicable.

Use of artificial intelligence

Not applicable.

Declarations

Author declares that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

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