



Application of Machine Learning in Horticulture

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Abstract

The development of machine learning (ML) technologies in recent years has opened new opportunities for the horticulture sector, enabling more precise, efficient and sustainable crop management. The aim of this publication is to review the applications of machine learning techniques in horticulture, with particular emphasis on image analysis, decision support systems, yield prediction and resource management. The most commonly used algorithms are described and their potential and challenges related to implementation in the horticultural context are discussed. The work also indicates areas requiring further research that can contribute to increasing productivity and minimizing the impact of agriculture on the environment.

Keywords: Machine Learning; Neural Networks; Decision Tree Algorithms; Clustering Methods; Image Analysis; Deep Learning Algorithms; Support Vector Machines; Optimization; Regression Model; Robotics; Precision Planting; Deep Yield

Abbreviations: ML: Machine Learning, CNN: Convolutional Neural Network, SVM: Support Vector Machines, LSTM: Long Short-Term Memory, IoT: Internet of Things, GIS: Geographic Information System

Introduction

Horticulture plays a key role in food production and maintaining biodiversity [1]. In the face of climate change, population growth and pressure to optimize resources, this sector requires modern tools to support production and minimize the risk of losses [2,3]. Machine learning (ML), which is one of the areas of artificial intelligence, allows the use of large data sets to solve complex problems that would require time and resources in traditional systems [4-6]. Machine learning includes techniques such as neural networks, decision tree algorithms, clustering methods and image analysis, which are used in key areas of horticulture, such as disease detection, fertilization optimization or yield forecasting [7,8].

Methodology

The analysis is based on a review of scientific literature and industry reports on machine learning applications in horticulture. In particular, empirical studies from recent years that demonstrate practical implementations of ML methods in various subfields of horticulture are analyzed.

Machine Learning Applications in Horticulture

Image analysis in plant disease detection [9,10]

The use of machine learning in image analysis is becoming a key element of precise monitoring of plant health [11]. Deep learning algorithms, especially convolutional neural networks (CNNs), are commonly used to classify and identify plant diseases based on images of leaves, fruits or flowers [10]. The advantage of these solutions is the ability to automatically recognize diseases at an early stage, which allows for faster application of remedial actions, minimizing crop losses [12]. Examples of applications include detection of fungal diseases in strawberry crops or bacterial infections in tomatoes [13-15].

Decision support systems [16]

Machine learning is supporting the development of decision support systems that can integrate data on weather conditions, soil moisture, and mineral composition to optimize production

processes [17]. Machine learning models can predict water needs, determine optimal fertilizer rates, and suggest harvest times [18]. Techniques such as linear regression algorithms, decision trees,

and support vector machines (SVMs) are often used to predict variables that affect crop performance, allowing growers to make more informed decisions [19] [Figure 1].

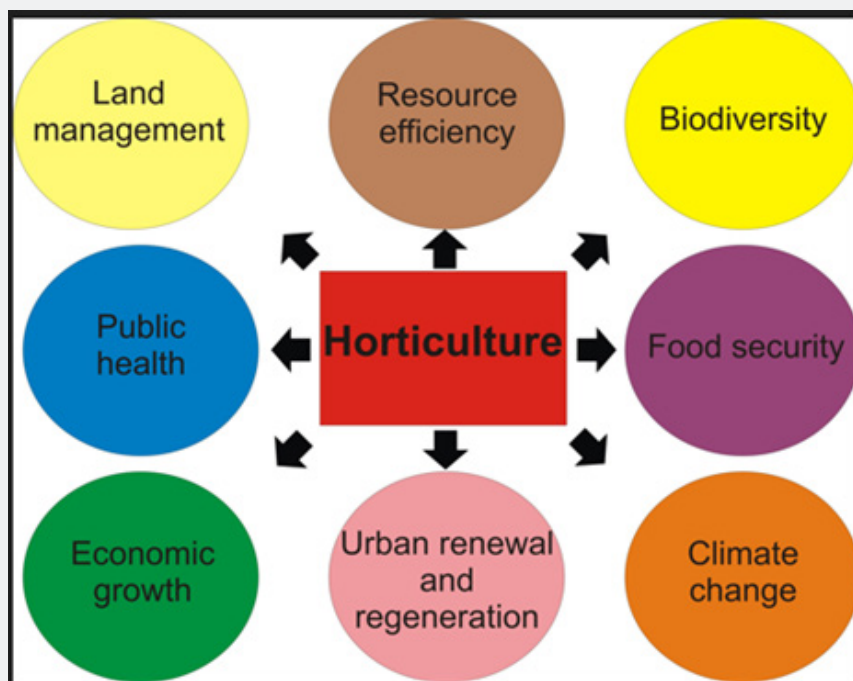


Figure 1: The impact of gardening on selected areas of life.

Yield forecasting and resource optimization

Predictive models based on data collected from sensors and historical meteorological data allow for precise forecasting of crop yields [20,21]. Methods such as random forest and gradient boosting trees are used to take into account many factors affecting crop yield, including temperature, precipitation and soil composition [22]. These forecasts not only increase operational efficiency, but also allow for sustainable resource management. Recent research shows significant successes in using ML for yield and quality trait prediction, particularly through multi-omics approaches. By integrating genomics and phenotypic data, machine learning models can predict complex traits, aiding in crop breeding. This approach has been applied effectively in several crops, such as rice and tomatoes, to improve the selection process in breeding programs [23].

Monitoring and optimizing fertilization and irrigation

In the context of fertilization and irrigation optimization, machine learning uses models based on the analysis of temporal and spatial data to adjust fertilizer rates and water volume to the current needs of plants [24,25]. These techniques include LSTM (Long Short-Term Memory) neural networks, which are used in the analysis of data sequences [26,27]. Optimal adjustment of

water and fertilizer amounts in real time allows for increased production efficiency while reducing resource consumption [28].

Robotics and automation

Robotics integrated with machine learning enables the automation of processes such as harvesting, pruning and sorting [29]. Robots equipped with image recognition and classification algorithms can automatically identify ripe fruits and vegetables, allowing them to be harvested at the optimal moment [30]. An example is the robots used in greenhouses for picking tomatoes, which can operate 24/7, increasing the efficiency and quality of the harvest [31].

Implementation examples and case studies

Plant Health Monitoring System – Precision Planting [32,33]

Precision Planting is an example of a horticultural production support system that integrates data from drones and soil sensors, and then uses CNN algorithms to analyze the image to assess the health of plants. This system allows for the detection of diseases and nutrient deficiencies at an early stage. Machine learning, especially deep learning models, is widely used in early disease detection by analyzing images of plant leaves. These models are capable of identifying symptoms of various diseases, facilitating

timely interventions to reduce crop loss. For instance, Ferentinos [34] developed a deep learning model capable of accurately diagnosing plant diseases based on leaf imagery. Machine learning models are also integrated with high-throughput phenotyping to assess plant growth and stress responses under diverse environmental conditions. By using image analysis and sensor data, these models can monitor and analyze traits related to plant stress and growth patterns, allowing for efficient resource management and adaptive crop management [35].

Strawberry Yield Forecasting Model – Deep Yield [36,37]

The Deep Yield project uses deep learning models to predict strawberry yields based on historical temperature, moisture, and fertilization data. Analysis showed that the system provided more accurate predictions than traditional methods, allowing farmers to better plan resources and harvest operations. One of the major challenges in applying ML in horticulture is integrating multi-layered data (e.g., genomic, transcriptomic, and environmental data) and addressing issues like overfitting and model interpretability. The complexity of ML models, especially

deep learning, often results in “black-box” predictions that lack transparency, making interpretability an ongoing area of research [38].

Challenges and future development directions

Data Complexity and Technology Cost

Implementing machine learning-based systems requires a large amount of data that must be properly stored, processed, and analyzed. The costs of acquiring advanced sensors, drones, and other devices can be a barrier, especially for smaller farms. In this context, the development of open data platforms and the availability of cheaper sensors can contribute to increasing the accessibility of the technology.

Scalability and adaptation of models

Machine learning models often require adaptation to specific local conditions, meaning that implementing a solution developed in one region is not always effective in another. Scalability of models and their adaptation to different types of crops, soils and climates remain significant challenges [Figure 2].

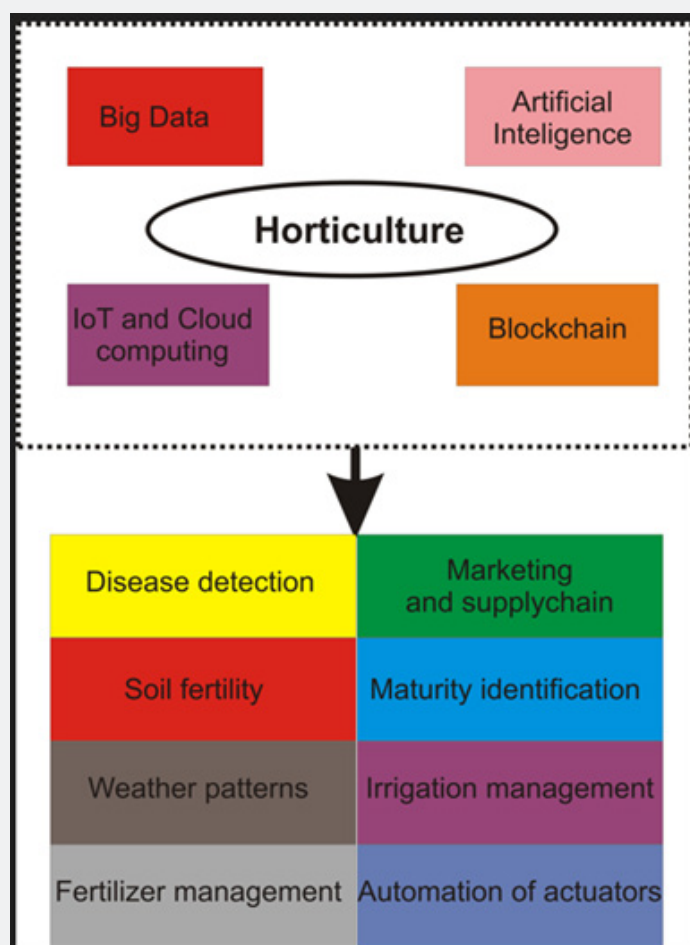


Figure 2: The most important aspects in which machine learning has been applied.

Integration with other digital technologies

Combining machine learning with the Internet of Things (IoT), Geographic Information System (GIS) systems and big data is a direction that can enable even more precise resource management and crop monitoring. Integration of these technologies will allow for automatic data collection and faster decision-making in real time.

Summary

Machine learning in horticulture opens up new possibilities for increasing production efficiency, contributing to more sustainable resource management. Thanks to the ability to analyze large data sets and the use of advanced algorithms, ML supports food production by precisely monitoring plant health, optimizing irrigation and fertilization, and automating work. Despite the existing challenges, further development towards the integration of digital technologies and adaptation of models to local conditions can contribute to the sustainable growth of the horticultural sector, which is especially important in the context of increasing environmental pressure and demand for food products.

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