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Review Article

Envisioning the Future of Intelligent Horticulture: A Theoretical Exploration of Deep Learning's Transformative Potential

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Abstract

Horticulture is an essential addition to the growth in the economy of any nation. In light of increasing populations, fluctuating environmental variables, and finite resources, meeting the dietary needs of the current populace has become an increasingly difficult endeavour. Horticulture has recently transitioned from an input-intensive to a knowledge-intensive sector due to the fact that vast quantities of information related to Horticulture can be preserved, shared, and examined to generate insights. An in-depth review of advancements in the swiftly progressing domain of deep learning is offered. Cognitive Horticulture, also referred to as precision Horticulture, has surfaced as a novel approach to tackle modern hurdles in Horticulture sustainability. Deep Learning is the process by which this cutting-edge technology operates. It imparts learning capability to the machine that doesn't need explicit programming. A key component of the impending Horticulture revolution is DL and Connectivity of Things (IoT)-enabled Horticulture gear. It is suggested that an article be written that offers a thorough analysis of machine learning's applications in Horticulture. The primary areas of research are agricultural yield prediction, disease and weed detection in crops, species identification, and prediction of soil parameters including moisture content and biological matter. This article provides a thorough analysis of the literature on the use of machine learning to horticultural production systems.

Keywords: Horticulture; Economic Growth; Sustainability; ML Applications; Deep Learning; Edge Technology; Data Analytics

Introduction

The Horticulture sector is fundamental to the worldwide financial system. As the human population continues to grow, there will be an added burden on the Horticulture system. Agri-technology and precision gardening, which are presently referred to as digital Horticulture, are emerging areas of science that leverage data-intensive techniques to improve Horticulture output while reducing ecology repercussions [1]. A multitude of sensors produce the data utilised in contemporary Horticulture processes. This understanding makes it easier to understand both the procedure itself (machinery information) and how it operates (varying crop, soil, and temperatures). Decisions taken in Horticulture are thus carried out more quickly and with higher levels of accuracy.

With the introduction of Machine Learning (ML), big data, or computing with high performance, new opportunities have emerged for understanding, measuring, and interpreting knowledge-intensive operations in Horticulture operational environments. One of the applications of machine learning (ML) as a scientific field is that it allows computers to learn without explicit programming. Biotechnology is among the many scientific fields where machine learning is being used more and more.

Application findings in the fields of Horticulture are expected to proliferate due to the expanding simplicity of use and success of deep learning in other domains. This review’s structure is determined by three categories of suggestions in an effort to provide direction for similar works

- **By implementing deep learning:** This article aims to provide an overview of object detection frameworks, a foundational understanding of machine perception concepts and terminology, and a critique of deep learning-based fruit detection approaches [2]. It is possible to trace the evolution of frameworks and detectors over the past few years, during which detecting speed as well as precision have increased significantly.
- **Sets of common images:** Annotated picture datasets that are publicly available, such as ImageNet, Microsoft’s Common Objects in Contextual (COCO), and the PASCAL Visual Objects Class (PASCAL VOC), have shown advantages for deep learning. The data sets, which include hundreds of popular item classes and millions of photos, are made accessible to programmers for the use of model training and algorithm evaluation in object recognition. Regretfully, there are no pictures of landscapes in those data sets.
- **Orchard produce projection:** Considerable scholarly effort has been dedicated to enhancing the precision of algorithms designed to determine the number of fruits present in images of canopy of trees. There have been fewer reports of efforts to establish a correlation between image fruit counts and the actual produce of an orchards block. Consequently, methods for addressing the problem of occluded produce are investigated as well.

CNN and Deep Learning: A Review

Convolutional Networking (convNets) are extensively employed in image processing tasks due to their capability of acquiring translationally invariant patterns, which enables the detection of objects irrespective of their location within an image, and their capability to extract intricate visual concepts via the detection of a hierarchical structure of progressively complicated patterns [3].

Machine learning presents enormous potential as a data processing instrument. Nevertheless, conventional approaches to machine learning frequently require the manual extraction of features. As the number of enormous datasets has grown and Graphic Processing Units (GPUs) have become more prevalent, algorithmic techniques and strategies have been continuously enhanced [4]. By integrating “further” (more complex) structures into models to robotize extricating highlights from natural information, profound learning has shown better execution than conventional AI strategies for specific grouping and expectation undertakings. In order to represent data in a structure that is hierarchical, a variety of nonlinear functions may be implemented at various levels of abstraction. This attribute has been demonstrated to be advantageous in enhancing the modelling efficacy for numerous comprehensive data analysis efforts.

In the area of artificial intelligence, AI- derived models are regarded as fundamental deep-learning techniques that have contributed to developments in image processing as well as analysis. Deep, feed-back Artificial Neural Networks (ANNs), of which CNNs are a subset, are a family of neural network structures with multiple layers that have been effectively implemented in computer vision tasks.

At this time, CNNs are acknowledged as one of the biggest and most influential machine learning strategies for the analysis of massive amounts of data across a vast array of scientific disciplines. The use of CNNs and derivatives of them in horticultural comprises a significant portion of the papers examined (92.86%, or 65 papers) [5]. Figure 1. Convolutional Neural Networks (CNNs) generally comprise several standard components, such as fully connected layers, convolution, and pooling, which connect simultaneously in various configurations to execute complicated learning tasks.

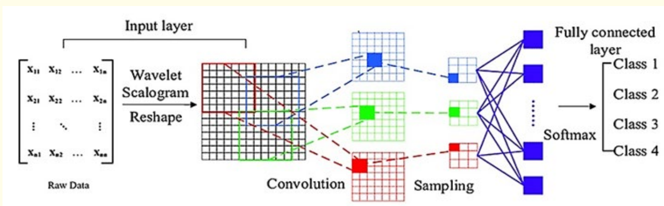

Figure 1: An input layer, convolution layer, Max pooling, and fully-connected neural network layer that outputs the activation function are typical of a convolutional neural network architecture.

We require horticultural crops including fruits, vegetables, herbs, perfumes, and decorative plants. With contemporary civilization, Horticulture crops shape human culture, enhance landscapes, and influence lives in addition to supplying sustenance. Horticultural workers generate more types and better goods due to this job transition, which is growing more significant. It also pushes horticulture researchers to work more practically to enhance crop functionality.

AI used in Horticulture production

Nowadays, horticulture crop production faces climatic issues such as rising temperatures and the possibility of frost, which might result in crop loss. With the progress of AI, methods for forecasting changes in environmental conditions are now accessible, allowing farmers to take the required precautions to safeguard their crops, whether by early harvesting or other ways. This technology may also be used in greenhouses to monitor and manage environmental conditions inside the building [6]. A business called as Sentiment had devised a system that can carefully evaluate the parameters that include light intensity, temperature, salinity, and water stress, and can warn for deviations if found, which may provide favourable conditions for plant development.

We present an in-depth review of machine learning's applications for Horticulture in this post. Numerous relevant studies are provided, highlighting important and unique characteristics of widely recognized ML models.

Tables 1 list the numerous acronyms that appear throughout this paper, which are categorized into methods of Machine Learning (ML), statistical measures, and generic abbreviations, respectively, due to the massive number of abbreviations applied in the associated scientific publications [7].

Abbreviation	Model
ANN	Artificial neural networks
BM	Bayesian models
DL	Deep learning
DR	Dimensionality reduction
DT	Decision tree
IBM	Instance-based models
SVM	Support vector machine

Table 1: Methods for the Machine Learning Framework.

Machine Learning (ML)

ML techniques often use a learning strategy that aims to learn from "experience" (training data) to accomplish a job.

In the world of machine learning, data is a collection of instances. Typically, an example is characterized by a collection of qualities, commonly referred to as features or constants.

The ML model's success in a particular job is assessed by an efficiency measure that improves with experience over time figure 2 [8]. Several statistics and mathematical approaches are used to assess the effectiveness of machine learning models and methods.

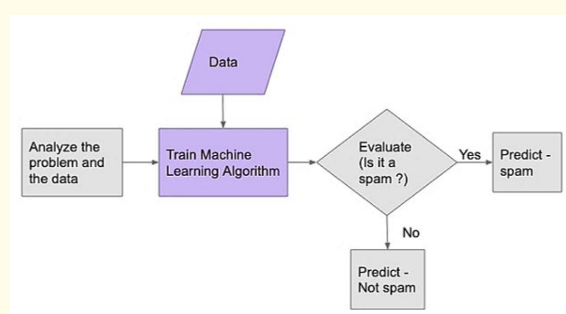

Figure 2: A common machine learning technique.

Impact of AI and IOT in horticulture

At the 1956 Dartmouth Conference, John McCarthy coined the term artificial intelligence (AI), describing it as a science and technical process for producing intelligent devices, particularly clever programming for computers. Artificial Intelligence (AI) technology endows machines with computing intelligence, enabling them to fully understand, analyse, and react to surroundings [9]. Artificial Intelligence (AI) encompasses several subfields, such as vision in computers, fuzzy reasoning, systems of experts, machine learning, deep learning, natural language processing, and Swarms Intelligent (SI), as seen in figure 3.

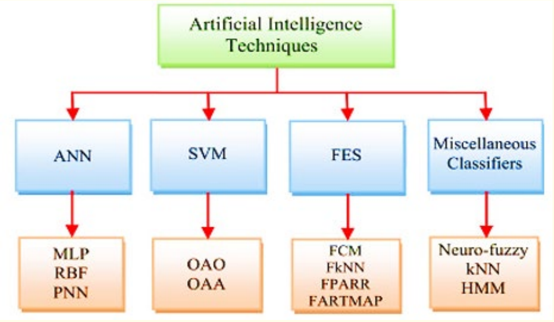

Figure 3: AI Technology.

The important variances between this review research and earlier works on the subject are shown in table 2. The paperwork has been organized as follows.

S. No.	Paper	Keywords
1	Sharma., *et al.* [11]	Ref. [11] Improvements in intelligent farming and precise Horticulture provide critical tools for addressing Horticulture sustainability difficulties. Based on the research results, a ML-based framework for long-term ASC is provided.
2	Usha., *et al.* [12]	Ref. [12] The same data may be analysed in several ways for different purposes. The possible application of RS approaches in Horticultural will be briefly addressed in order to harness the current technologies for optimal crop management.
3	Saedi., *et al.* [13]	Ref. [13] This result demonstrates that the framework is well-developed and has strong generalizability. This model's processing time was roughly 8 Ms per picture, compared to 351 Ms for ResNet152, demonstrating that the suggested network is substantially superior for real-time applications.
4	Ariesen-Verschuur., *et al.* [14]	Ref. [14] This report summarizes the findings from a thorough literature assessment on digital-twin applications for greenhouses horticultural. The research reveals 8 papers that directly address the application of Digital Twins in greenhouse horticulture and 115 studies that indirectly apply the Digital Twin idea to smart IoT-based systems.
5	Longchamps., *et al.* [15]	Ref. [15] This study discusses yield estimation methodologies that may be classified as proximal, either indirect or direct, and distant measuring concepts. It discusses remote sensing as a method for estimating and forecasting yield prior to harvesting. This analysis revealed the need for new commercial methods to map horticulture crop yields.

Table 2: Significant distinctions between the published papers and the article.

Method

First, the evaluated articles were divided into four main categories: soil management, water management, animal management, and horticultural management. Based on their intended purpose, machine learning applications in the horticulture industry were categorized into smaller areas. These applications included identifying plants, predicting production, detecting diseases, assessing crop quality, and identifying species. Animal welfare and livestock production were found to be the two distinct areas for machine learning applications in the livestock business.

World Science Direct, Scientific Nature, PubMed, Scopus, Google Scholar, and Natural were the main search engines that were employed. The selected papers concentrate on works that are generally published in journals. Despite being crucial to Horticulture output, climate prediction was left out of the assessment that was presented, despite the fact the use of Machine Learning (ML) approaches for predicting climates are a distinct discipline. Lastly, everything that is written here relates to the years the year 2004, until the present day.

Forecast productivity

Yield prediction is one of the most significant problems in precision horticulture. It is essential for mapping and forecasting productivity, balancing crop demand versus supply, and controlling crops to maximize production. Table 3. One efficient, inexpensive, and non-intrusive machine learning program was able to count the amount of caffeinated fruits on a branch on its own.

Article	Crop	Observed feature	Functionally	Models/algorithm	Results
[16]	Coffee	Fourty-two (42) colors appear in digital photographs of coffee fruits.	Automatically counts coffee fruits on a coffee branch.	SVM	Harvestable: (1) Ready or overripe: 85.54-83.83% deceivability rate (2) Semi-ready: 98.25-89.32% deceivability rate. 1) Unripe: 76.91-82.38% deceivability rate.
[17]	Green citrus	Picture credits (from 20 x 20 pixel advanced photos of unripe greenish citrus organic products) incorporate unpleasantness, contrast, direction, line-similarity, consistency, flaws, and level of detail, anomaly, radiance, non-abrasiveness, and fineness.	ID of how much youthful greenish citrus organic product according to normal outside conditions.	SVM	89.4% accuracy
[18]	Grass	Vegetation pointers, the ghostly groups of red and infrared.	Assessed green creation (kg dry matter/ha/day) for two treated prairie ranches in Ireland: Moorepark and Granger.	ANN/ANFIS	Moore Park: R 2 = 0.88 RM.SE = 15.07 Grange: R2 = 0.76 RM.SE = 15.55.
[19]	Tomato	High spatial resolution in RGB photos.	Location of tomatoes utilizing RGB photographs recorded by UAV.	Clustering/EM	Recall: 0.6866. Precision: 0.6191; F-Measure: 0.7305.
[20]	Rice	Horticultural, surface meteorological, and soil physicochemical information, including yield or improvement records.	Rice development stage and yield estimate.	SVM	Center season rice: RMSE (kg h−1 m2) = 128.8; Headed stage: RMSE (kg h−1 m2) = 98.4; Dairy stage: RMSE as (kg h−1 m2) = 139.4; Early rice: RMSE (kg h−1 a2) = 89.3; Headed stage: RMSE (kg h−1 m2) = 69.0 Cow stage: RMSE (kilograms h−1 m2) = 32.4. Late rice: developing stage: the RMSE (kg h−1 m2) = 88.2; headed stage: RMSE (kg h−1 m2) = 59.7. Milk stage: RMSE (kg h−1 m2) = 46.5.
[21]	General	Horticultural data: meteorological, financial, and natural factors and reap.	Strategy for solid assessment of agrarian yield gauges.	ANN/ENN and BPN-based.	1.3% error rate.

Table 3: Summarizes the aforementioned studies for the yield prediction sub-category.

Weed detection

Weed identification and control is another major issue in Horticulture. Weeds, according to many growers, are the greatest serious hazard to Horticulture productivity. Weeds are challenging to recognize and recognize from crops, accordingly viable distinguishing proof is basic for maintainable horticulture. Once more, ML calculations joined with sensors might bring about exact weed ID and characterization at a modest expense, with no natural troubles or secondary effects. ML for weed recognizable proof might assist with planning instruments and robots to eliminate weeds, lessening the interest for pesticides. Two examination on AI applications for weed recognizable proof difficulties in horticulture were introduced.

The primary objective was to accurately recognize and discriminate between these species for both ecological and financial reasons. Table 4. The authors developed a weed identification approach that utilizes SVN in grassland crops.

Article	Observed feature	Functionally	Models/algorithm	Results
[22]	Phantom groups including red, green, and NIR, as well as the surface layer	Recognizable proof and planning of Silybum marianum.	ANN/CP	98.87% accuracy.
[23]	Otherworldly parts of hyperspectral imaging.	Recognizable proof and separation of Zea mays and types of weeds	ANN/one-class SOM, Clustering/one-class MOG	Zea mays: SOM rises to 100 percent precision MOG approaches 120 percent exactness. Weed species: SOM = 58-94% exactness. MOG: 38-88% exactness.
[24]	Camera shots of grass and other weed assortments.	Report on the exhibition of order frameworks for grass versus weed identification.	SVN	98.9% Once more, Rumex grouping 4.68%. Urtica characterization: 98.1% for blend weed and blended climate conditions.

Table 4: Summarizes the preceding studies for the instance of weed identification sub-category.

Evaluation and evaluation of knowledge-based horticulture systems.

In this part, the ML algorithms employed by various researchers in the accuracy of the Horticulture system are discussed [10]. The Horticulture business faces several issues across the globe, and a knowledge-based Horticulture model enables farmers to make sustainable use of resources while maximizing production from Horticulture land. Figure 4 depicts the categorization of goods based on the many uses of precision Horticulture.

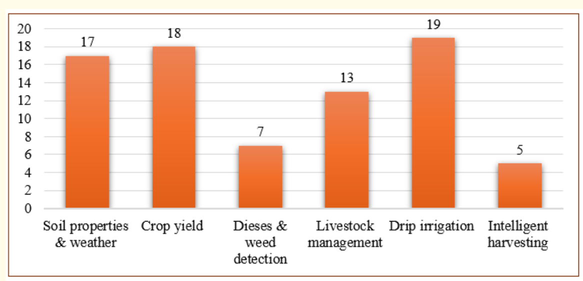

Figure 4: Classification based on Horticulture cycles.

All of the distributions of the machine learning and deep learning models used by precision Horticulture researchers is shown in figure 5 [11].

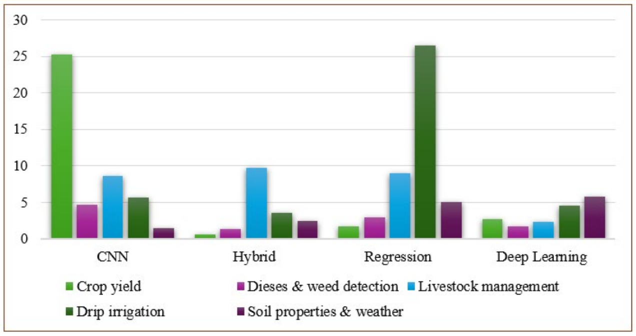

Figure 5: Machine learning methods utilized in precision Horticulture applications.

Figure 6 illustrates the implementation of CNN, ANN, and RNN algorithms in precision horticulture. The researchers employed approximately ten diverse DL/NN algorithms for prediction and classification throughout the assessed research. However, figure 6 specifically highlights and presents the eight most frequently used techniques. The remaining two algorithms, namely LeNet and Caffee, are categorized into various groups and are employed as supporting or comparative algorithms.

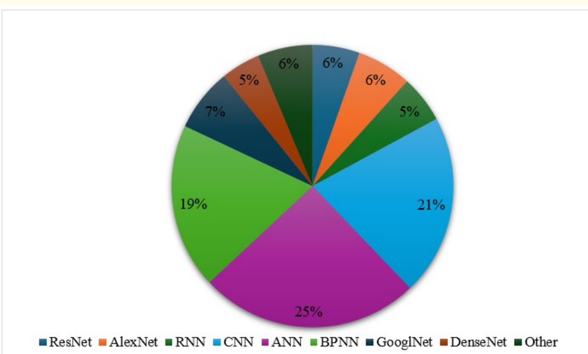

Figure 6: Classification algorithm for precision Horticulture.

AI'S problems and limitations in accuracy the horticulture sector

Artificial intelligence has an opportunity to play a significant role in satisfying the world's food requirements [12-30]. However, there are several problems that are impeding its implementation in Horticulture businesses, which are detailed below

- Ineffective educational attainment among Indian farmers making it challenging to bridge the divide between them and technological advances, corresponding to a recent governmental survey.
- Farmers lack motivation to gain digital skills for better Horticulture practices.
- The greatest number of Horticulture fields are situated in rural areas. In remote areas with inconsistent internet connectivity, integrating IoT architecture and WSN—which need the use of cloud computing services to handle data processing and storage—is very difficult.
- Machines' cognitive abilities make accurate prediction and categorization challenging in different regions.
- The initial setup of digital farming, including gear and software, demands significant investment.
- Deploying smart sensors and electrical devices consumes significant energy.

Conclusion

Farmers may use precision Horticulture to maximize yields with precise inputs by using technology. Smart actuators enabled by the Internet of Things, sensors, satellite images, robots, and unmanned aerial vehicles are a few of the notable technological innovations that have benefited the Horticulture industry. Additionally, the data demonstrates that SVM and ANN machine-learning models were used in the bulk of the study. More specifically, SVMs were used for managing livestock whereas ANNs were used for Horticulture, water, and soil management. In horticultural research, algorithms that use deep learning provide a powerful tool for data absorption and have shown promise in addressing the present challenges of accurately estimating plant conditions, accurately recording plant progress, and quickly identifying product quality.

Future Work

Future research might build NLP-based systems for Horticultureists, and more ML, DL, or combination algorithms could be investigated in Horticulture to make sustainable use of the resources currently in position.

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