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Artificial intelligence-assisted technologies in horticultural crop management

Horticultural crops are essential for human well-being, as they provide crucial nutrients that support a balanced diet, enrich cultural landscapes, and contribute to nutritional security. To meet the demands of growing population, it is imperative to enhance both the quantity and quality of horticultural produce while considering limited stakeholder values. Integrating artificial intelligence (AI) into horticultural crop management is essential for optimizing productivity, diagnosing diseases, and enhancing value-addition. AI can help understand domestication events, adaptation processes, yield improvement, pathogen detection, and resilience by rapidly analyzing vast amounts of data from high-throughput sensors, satellite imagery, and climate models. By assimilating diverse data sets, deep learning technologies offer reliable predictive outcomes for complex and uncertain phenomena. The applicability of advanced tools and technologies for significant improvements in horticultural crops and their monitoring through sustainable practices is discussed. These technologies facilitate effective classification and recognition of images of flowers, fruits, and vegetables, as well as phenotypic identification based on various attributes, enhancing productivity and economic returns. Furthermore, they leverage the horticulture industry through automated precision farming, predictive analytics, and supply chain optimization; ultimately promoting resource-efficient and sustainable practices to advance the Horticulture Sector.

HORTICULTURAL crops are essential for human well-being, as they provide vital nutrients, enhance food diversity, support ecosystem health through biodiversity, and contribute to economic stability and livelihoods through their cultivation and trade. These crops, which include fruits, vegetables, herbal medicines, and ornamental plants, play a crucial role in our daily lives. Effective management is essential to address various external challenges, such as soil quality, water availability, and temperature, which contribute to their high input costs. The cultivation of horticultural crops often relies on experienced labourers for tasks such as pruning, thinning, harvesting, and pest control. Moreover, these crops typically have shorter shelf-life, necessitating specific post-harvest timing and logistics that require specialized knowledge and techniques to maximize their market potential. Therefore, it is imperative to supplement the traditional workforce with technology and mechanization. This transition can be facilitated through smart farming techniques supported by big data analytics, artificial intelligence, and machine learning, ultimately enhancing horticultural production.

The integration of digital horticultural sensors–such as remote sensing technologies, the Internet of Things (IoT), thermal and near-infrared cameras, and X-ray imaging–has markedly enhanced data collection from orchards and groves. These technologies empower researchers to develop models based on the collected data, which can be applied to actual production processes. By monitoring the growth status of horticultural crops, these models can guide optimal management decisions, ensuring the growth process is effectively optimized. However, the rapid advancement of imaging sensors has resulted in an overwhelming volume of digital horticultural data, leading the horticultural science community to contend with a flood of irrelevant and redundant information. Consequently, it is crucial to develop suitable analytical technologies to extract valuable features from this unrefined data while addressing the practical challenges of translating these technologies into real-world applications. This review aims to explore the applications of artificial intelligence (AI), machine learning, deep learning, big data analytics, and decision trees in the context of significant horticultural crops. Additionally, it highlights recent AI tools and techniques designed to manage large data sets, encouraging their application to solve pressing problems and facilitating the transition towards a smart horticulture industry.

Applications of AI

Recognition and classification

The use of AI tools for flower recognition and classification is crucial for enhancing biodiversity conservation efforts, aiding agricultural practices by identifying plant varieties, facilitating ecological research, and supporting horticultural industries by optimizing breeding and cultivation processes. Convolutional neural networks (CNNs) have been employed to classify flower images using a database of 9,500 images, achieving a recognition rate of 97.78% across five batches of training and testing data, outperforming other classifier models on the same dataset. Additionally, a pre-trained CNN model has demonstrated high accuracy rates of 96.39 and 95.70% for flower species classification on two distinct datasets, Flower17 and Flower102, respectively. A novel classification method utilizing a binary classifier within a fully convolutional network framework has been developed to differentiate between various flower types, even among species with similar shapes and appearances. Moreover, a deep-learning approach for vegetable image classification was created using the AlexNet network model implemented in Caffe, resulting in a significant improvement in classification accuracy, reaching 92.1% on the test dataset compared to traditional back propagation neural networks. Deep learning models utilizing VGG16 and ResNet50 networks have also been employed to recognize large-flowered chrysanthemums, achieving remarkable recognition performance and speed. Overall, accurate identification of flower species can help prevent the spread of invasive species and improve landscape management, thereby contributing to environmental sustainability.

Fruits monitoring and classification

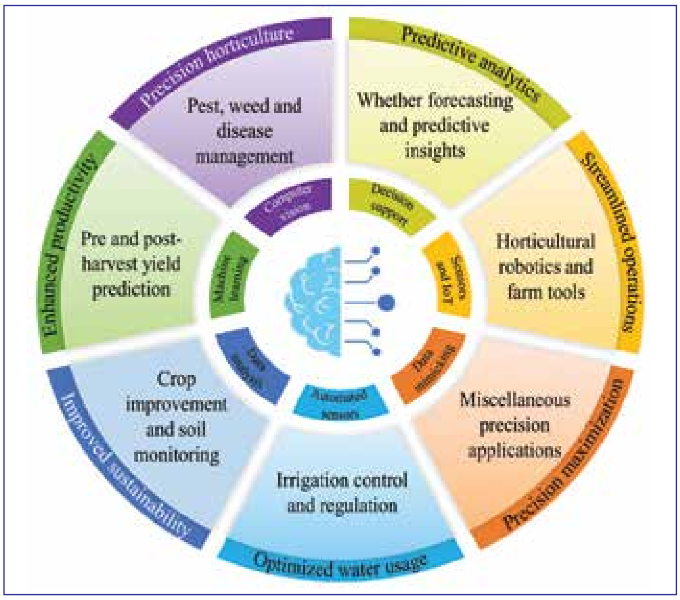
Mango: Real-time mango detection networks have been developed for mobile device processors, employing generalized attribution methods and pruning large networks using kernel attribution, while comparing weight size and computational efficiency with significant accuracy. The MangoYOLO deep learning algorithm detects mango fruits in each frame, while the Hungarian algorithm correlates fruits between neighbouring frames, enabling multiple-to-one assignments and improving mango fruit load estimation through a video-based Kalman filter method. A multilayer convolutional neural network (MCNN) has been proposed for classifying mango leaves infected by anthracnose fungus, validated on a real-time dataset of images and achieving higher classification accuracy compared to other state-of-the-art approaches. Additionally, a novel system employs an unmanned ground vehicle equipped with a hyperspectral sensor, navigation system, and LIDAR to map mango maturity at the orchard scale, facilitating precision farm management, selective harvesting, and harvest scheduling. Automated assessment of panicle count by developmental stage can significantly inform farm management practices. In this context, the YOLOv3-rotated model demonstrated greater accuracy for total panicle counts, while the R2CNN-upright model excelled in panicle stage classification. Furthermore, faster regional convolutional neural networks have been utilized to map mango flowering intensity and panicle counts per canopy across an orchard, enabling the identification of early flowering trees for selective early harvest.

Banana: The first deep learning application for clustered horticultural crops, specifically banana fruit tiers, has been successfully classified using a Mask R-CNN model, achieving an accuracy of 96.1% through data augmentation and improved classification techniques. An enhanced deep learning approach employing multiple Long Short-Term Memory (LSTM) layers with numerous neurons has been fully trained to forecast banana harvest yields effectively. Additionally, a deep learning-based method for detecting and counting banana plants has been developed using high-resolution images obtained from unmanned aerial vehicles. This approach utilized three image processing methods to enhance orthomosaic vegetation by generating multiple variants. Furthermore, a deep learning method for classifying banana leaf diseases, implemented using the LeNet architecture as a convolutional neural network (CNN), has proven effective under various conditions, including changes in illumination, complex backgrounds, and variations in resolution, size, pose and orientation of real scene images. The proposed CNN classification system has the potential for commercial development as a field-based automatic postharvest classification system for grading Cavendish bananas.

Grape: An innovative approach combining an integrated miniaturized spectrometer with support vector machines and convolutional neural networks has been employed to identify 64 grapevine varieties from a dataset of 35,833 samples, marking the first application of these technologies in grapevine variety identification. Furthermore, the use of transfer learning and fine-tuning techniques based on the AlexNet architecture has been explored for identifying grape varieties.

Apple and pear: A lightweight backbone network based on residual network architecture has been developed to enhance the real-time computational performance of network models, demonstrating effectiveness in the real-time detection and segmentation of apples and branches in orchards. Furthermore, the creation of a robust image labeling algorithm and an efficient deep learning detector, known as 'LedNet,' has enabled real-time and accurate apple detection in orchards, providing a fast and effective framework that has been validated. The development of a multi-task network, DaSNet-v2, has also achieved real-time and accurate fruit detection, segmentation, and 3D visualization in apple orchards.

An automatic method for identifying apple defects has been developed using laser-induced light backscattering imaging along with a convolutional neural network (CNN). The AlexNet model achieved a recognition rate of 92.5%, demonstrating superior accuracy compared to conventional machine learning algorithms. To classify apples into mealy and non-mealy categories, pre-trained convolutional neural networks AlexNet and VGGNet were utilized, achieving accuracies of 91.11 and 86.94%, respectively. An improved Mask R-CNN model utilizing the U-Net method has enabled instance segmentation of apple flowers across three different growth stages, incorporating image augmentation and segmentation



Overview of artificial intelligence-assisted tools and technologies, illustrating their potential as prerequisites for horticultural crop improvement through the integration of diverse functional aspects

under occlusion and overlap conditions. The proposed YOLO-V3 network, enhanced with DenseNet, allows for real-time detection of apples at three different growth stages in orchards, handling high-resolution images under occlusion and overlap.

Citrus: A novel technique employing small unmanned aerial vehicles (UAVs), multispectral imaging, and deep learning convolutional neural networks has been developed to evaluate phenotypic characteristics in citrus fruits. This method has proven successful in detecting and counting citrus trees and estimating canopy size with significant accuracy. Remote sensing is integral to precision agriculture, and UAVs are revolutionizing workflows for measuring crop conditions, identifying weeds, and conducting other agricultural assessments. A novel approach for yield estimation has also been proposed, leveraging long short-term memory (LSTM) networks for individual trees in commercial orchards. The fluorescent spectrum of citrus juice has been analyzed using a convolutional neural network (CNN), which generated an excitation-emission matrix (EEM) for fluorescence intensity. The °Brix/acid ratio of juice extracted from the flesh was estimated using CNN regression, yielding an absolute error of 2.48, significantly enhancing the accuracy of °Brix/acid ratio estimations.

Plum: To facilitate the automatic identification of plum varieties at early maturity stages–a task that poses challenges for human experts–a two-step procedure has been implemented. This process involves capturing images to identify the plum region, followed by determining the variety using a deep convolutional neural network, achieving an accuracy of up to 97%. Additionally, a deep learning tool has been developed for analyzing plum varieties through image analysis. This system can differentiate among three plum varieties–Red Beaut, Black Diamond, and Angeleno–with an effectiveness of 92.83%, reaching over 94% accuracy when tested independently on these varieties, which exhibit different ripening cycles. Furthermore, a classification system has been designed to categorize Horvin plums, including samples that may be visually impaired, providing an affordable and high-performance selection system for technology-deprived areas.

Strawberry: A strawberry flower detection system has been developed using a small unmanned aerial vehicle (UAV) equipped with an RGB camera. This system captures near-ground images of two strawberry varieties and generates orthoimages, which are then processed using Pix4D software and divided into sequential segments for deep learning detection. A faster region-based convolutional neural network (R-CNN) has been employed to detect and count the number of flowers, mature strawberries, and immature strawberries. Additionally, a robotic agriculture system presents a viable solution by training a network on synthetic data and subsequently testing it on real data. This algorithm utilizes a modified version of the Inception-ResNet architecture to effectively capture features across multiple scales, enabling efficient counting even in shadowy conditions.

Olive: A study involving 2,800 olive fruits from seven varieties utilized the Inception-ResNetV2 architecture for classification, achieving a top accuracy of 95.91% on external validation sets. This classifier, when integrated into industrial conveyor belts, represents an advanced solution for post-harvest olive processing and classification. The enhanced dataset used in this model distinguishes it from others in the field.

Blueberry: A convolutional neural network (CNN)-based image recognition method has been developed to identify the presence of trays containing living legacy blueberry plants, trays without living plants, and the absence of trays in the rooting stage, achieving high accuracy with trained models. Additionally, two deep learning models, ResNet and ResNeXt, have demonstrated superior performance over traditional machine learning methods in classifying fruit samples. This indicates their potential for online fruit sorting and highlights the effectiveness of deep CNNs in analyzing internal mechanical damage. Furthermore, fully convolutional networks were employed for hyperspectral image segmentation, with models trained without transfer learning outperforming those that utilized it, accurately predicting early bruising in blueberries.

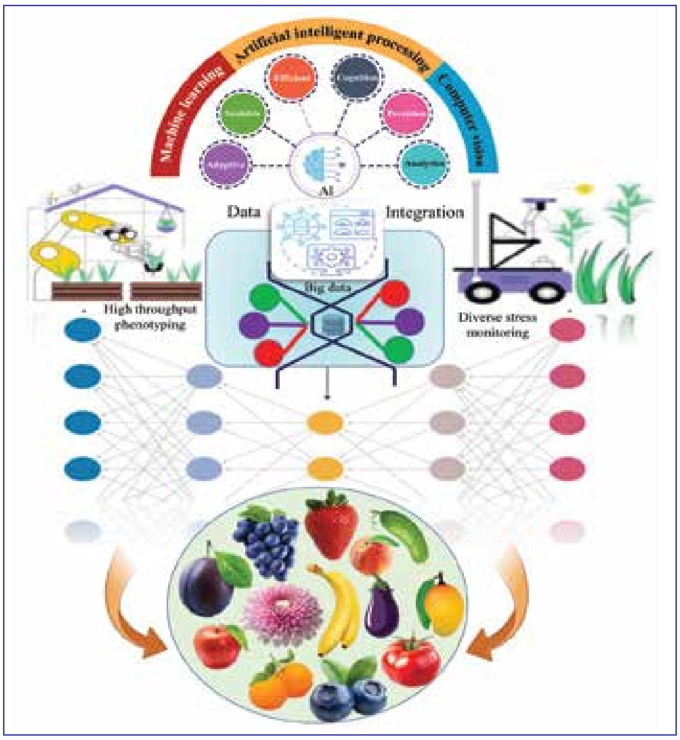
Cucumber: Cucumbers are characterized by their high water content, low calorie count, and rich nutritional profile, making them versatile horticultural produce widely used in culinary applications. A robust cucumber recognition algorithm has been proposed, utilizing I-RELIEF for feature analysis and a multi-path convolutional neural network (MPCNN) for feature extraction, along with a block-based strategy to enhance efficiency. This algorithm aims to enable automatic cucumber recognition for natural robot harvesting. Additionally, a deep convolutional neural network (DCNN) has been employed to identify four cucumber diseases based on symptom images, achieving commendable recognition results with field-captured disease images. The use of dilated convolutional kernels has increased the local receptive field and improved feature extraction, while a global pooling layer has reduced training parameters and mitigated overfitting, leading to enhanced recognition accuracy and robustness.

Potato: Machine vision and image processing methods are critical for identifying defects in agricultural products, particularly in potatoes. A potato disease classification algorithm has been developed that employs deep learning and computer vision techniques to identify and classify plant diseases. This algorithm utilizes a deep convolutional neural network (CNN) to classify tubers into five categories: four disease classes and one healthy potato class. CNN methods were successfully applied to classify five potato diseases–Healthy, black scurf, common scab, black leg, and pink rot–using a database of 5,000 potato images, achieving accuracies of 100 and 99% in certain classes.

Tomato: A deep learning-based method for ripe tomato detection has been proposed, effectively distinguishing between targets and overlapping tomatoes to identify individual fruits. An improved method for tomato organ detection employs a convolutional neural network (CNN) to identify key organs in tomatoes using deep migration learning in complex backgrounds. In greenhouse settings, the Mask R-CNN algorithm has been utilized to detect tomatoes in images, successfully identifying objects and their corresponding pixels. This study demonstrated that the performance of the RealSense camera in detecting tomatoes is comparable to laboratory conditions when utilizing higher-resolution images.

Onion: A novel image-based field monitoring system has been developed for the automatic detection of onion disease symptoms using deep neural networks. Trained with weakly supervised learning, the system achieved the highest mean Average Precision (mAP) at an Intersection over Union (IoU) threshold of 0.5, resulting in significant time and cost savings in field crop cultivation.

Miscellaneous horticulture crops: For peaches, a deep belief network (DBN) model outperformed the partial least squares discriminant analysis model, achieving the highest accuracy in classifying decayed peaches into three stages: slight, moderate, and severe. In tulips, a Faster R-CNN network was applied to experimental data, yielding results nearly identical to those obtained using previous methods that relied solely on RGB data for the automatic detection of Tulip Breaking Virus. For dates, a novel method utilizing a convolutional neural network (CNN) was developed to distinguish healthy date fruits from defective ones, achieving an overall classification accuracy that surpassed traditional feature engineering methods. In jujubes, a deep learning approach was employed to detect subtle bruises on winter jujubes using pixel-wise spectra extracted from hyperspectral images across two spectral ranges. This innovation could lead to the development of an online system for detecting bruises on winter jujubes in the future. Additionally, pre-trained deep learning models, including AlexNet and VGG16, were utilized to classify five diseases and a healthy plant in eggplants using smartphone images. The modified architecture of VGG16 achieved an average validation accuracy of 96.7%, while the adjusted model recorded an accuracy of 93.33% when tested with field samples. For passion fruit, the feasibility of detecting fruits using depth images was explored, resulting



Improved horticultural produces

in the development of a Faster R-CNN-based RGB-D detector that identified five growth stages with significant detection rates and classification accuracy. In lettuce, new analytical functions have been developed to map lettuce size distribution across fields, enabling farmers and growers to implement precision agricultural practices based on GPS-tagged harvest regions.

SUMMARY

AI technology is increasingly gaining attention in horticultural sciences due to the rapid expansion of data availability. It serves as a powerful tool for data assimilation, enabling objective recording of plant growth, accurate assessment of plant status, and swift detection of product quality. Successful large-scale implementation hinges on effective collaboration between computer scientists and horticulturists, seamless integration of data collection processes, and a robust curation pipeline. The development of a computational ecosystem designed to facilitate planting, intelligent orchard management, and address existing bottlenecks within the horticultural sector has been discussed. We also explore the potential commercialization of solutions such as automated robots employing faster region-based CNNs for tasks including transplanting, fruit picking, and yield estimation.

Illustration of the key pillars of artificial intelligence and how high-throughput phenotyping, along with other integrated functions, enhances net productivity in horticultural crops by overcoming limiting factors such as climate variability, soil quality, and effective input-output trade-offs.

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