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ARTIFICIAL INTELLIGENCE AND DEEP LEARNING IN FLORICULTURE AND LANDSCAPING: ADVANCES, APPLICATIONS, CHALLENGES AND FUTURE PERSPECTIVES

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ABSTRACT

Floriculture and landscaping are closely related branches of ornamental horticulture and share many underlying technologies but are seldom reviewed together. This review synthesises recent literature on the application of artificial intelligence (AI) and deep learning in the floriculture value chain, landscape planning and design. Convolutional neural networks, object-detection frameworks (YOLO, Faster R-CNN) and vision transformer and self-supervised models have been used in floriculture for cultivar identification, high-throughput phenotyping, flower and bud detection, growth and flowering prediction, disease and pest detection, quality assessment, robotic harvesting, grading and sorting and postharvest management including vase-life prediction. In landscaping, AI is assisting in generative design and visualisation, sensor-based plant selection and machine learning-GIS approaches to green-space planning. Recognition, grading and disease scoring are now image-based tasks often more than 90% accurate and faster than manual assessment. But even in the best greenhouse conditions, robotic harvesting still only succeeds in about 78 to 80 percent of cases and landscape tools are used mainly as decision-making aids rather than as autonomous planners. Some of the limitations that hinder widespread use include lack of annotated ornamental datasets and high cultivar diversity, poor generalisation between laboratory and field conditions, cost limitations for small and medium growers, limited model interpretability, lack of standardised benchmarks and challenges in handling delicate plant material. Future directions include multimodal and generative decision-support systems that combine computer vision and large language models, explainable and lightweight edge models, IoT-linked digital twins, soft robotic manipulators and shared data ecosystems integrated with plant breeding. This review provides a consolidated roadmap for researchers, growers and policy makers toward intelligent, sustainable ornamental horticulture.

KEYWORDS: artificial intelligence, deep learning, floriculture, landscape design, computer vision, precision horticulture

1. INTRODUCTION

Floriculture, the production of flowering and ornamental plants for sale as cut flowers, potted plants and landscape plants, is one of the most important and technically demanding segments of modern horticulture. The global cut flowers market alone was valued at approximately USD 35 billion in 2023 and is projected to reach USD 50.1 billion by 2030, growing at a CAGR of 5.3% (Research and Markets, 2024). Including potted and nursery stock, the larger flower and ornamental plants market is estimated even higher, with some analyses predicting growth to USD 83.47 billion by 2030 (The Business Research Company, 2026).

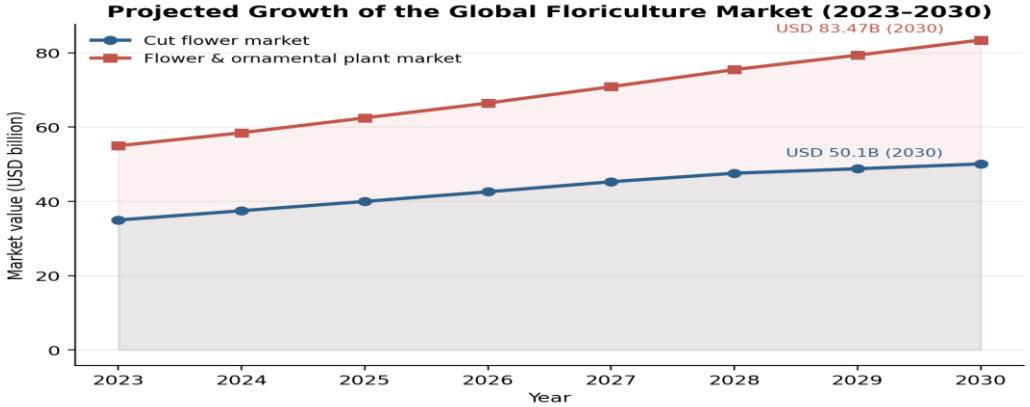


Figure 1. Projected growth of the global cut flower and ornamental plant market, 2023–2030

For a long time, traditional floriculture management relied on the knowledge of experienced growers. It often involved manual visual inspections to identify diseases and intuition-driven design choices in landscaping. However, the large scale of modern horticultural operations, the labour-intensive nature of quality checks after harvesting and the complexities of managing multiple environmental factors have highlighted the limits of these purely human methods. These challenges have created a push for using computational intelligence.

In the last decade, the rapid development of artificial intelligence, especially the deep learning boom driven by large image datasets and powerful graphical processing units (GPUs), has led to significant improvements in visual recognition, predictive analytics and automated decision-making. The use of convolutional neural networks (CNNs) with plant images has shown impressive accuracy in identifying species, classifying diseases and extracting morphological traits (Abbas *et al*., 2022; Jafar *et al*., 2024). More recently, vision transformer (ViT) architectures, which were initially developed for natural language tasks have been adapted for detailed plant recognition. They have achieved classification accuracies above 99% on key datasets (Li *et al*., 2024a).

In landscape architecture, AI tools are being used to automate design workflows and create layout plans that consider ecological constraints. They also evaluate green space equity using satellite data along with machine learning classifiers (Ganjirad *et al*., 2025). The use of Internet of Things (IoT) sensor networks with AI controllers allows for real-time climate management in greenhouses. This can improve conditions for growing ornamental plants with little human involvement (Hasan *et al*., 2025). Despite these advancements, using AI and deep learning in floriculture and landscaping has many challenges.

This review brings together the current validated literature on artificial intelligence and deep learning that can be used specifically for applications related to floriculture and landscaping, two similar industries but also with many identical underlying technologies, but rarely reviewed together. In the following sections, we will explore, in order, the use of artificial intelligence and deep learning in the floriculture value chain from cultivar discovery and phenotyping to disease detection, harvesting, grading and postharvest handling and also their application in landscape design, plant selection and green-space planning. The review then examines the practical and technical challenges still to be overcome for these new technologies to become more widely adopted within ornamental horticulture before concluding with some potential future directions for this new discipline.

2. Applications of AI and Deep learning in floriculture

Deep learning has been applied in almost every step of the value chain in floriculture, from the nursery bench to the vase. Currently, convolutional neural networks and similar architectures are used for flower species, cultivar identification and measurement of phenotypic traits that would otherwise require tedious manual assessment, detection of disease and pest damage at early stages, robotic harvesting guidance, grading and sorting of cut flowers and potted plants to the standards of commercial quality (Yang *et al*., 2021). Much of this progress has been made by transferring model architectures and training strategies first developed for major food crops into the ornamental sector and then adapting them to the specific challenges of flowers, such as fine-grained colour and shape differences between cultivars, delicate and easily damaged plant material and product value based on visual perfection rather than just on size or yield (Mahmud *et al*., 2023).

2.1 Flower recognition and species identification

The classification of flowers is inherently fine-grained; for example, two varieties of chrysanthemum may differ simply in the curvature of their petals or in the colour of their yellow. A non-pre-trained ResNet18 with three parallel outputs (cultivar, petal type and flower type) was trained using photos of 213 large-flowered chrysanthemum cultivars gathered over two seasons. Since ImageNet pre-training tends to favour texture and is comparatively insensitive to color, a characteristic that distinguishes flowers they purposefully avoided using it. The trade-off is instructive: the model achieved 70.62% top-5 accuracy on photos from the next year, but the same cultivars were correctly ranked first much less frequently because a cultivar's flowers vary depending on the season and developmental stage (Wang *et al*., 2022).

For automated flower cultivar identification, machine learning-based picture recognition has shown significant promise. Principal component analysis (PCA), linear discriminant analysis (LDA) and support vector machine (SVM) were combined in Anthurium to reduce dimensionality, extract features and classify cultivars respectively. Using an RBF-kernel multi-class SVM, the system was able to obtain a classification accuracy of up to 99.5% using photos from 20 cultivars under variations in bloom size, orientation and illumination. As a basis for automated flower grading and high-throughput phenotyping in ornamental crops such image-based recognition techniques can enable quick and accurate cultivar identification (Soleimanipour *et al*., 2018).

The limitations of traditional morphology based and molecular methodologies are being overcome by the increasing use of deep learning and machine learning techniques for automated chrysanthemum cultivar identification. Image based systems can categorise various cultivars according to their phenotypic traits and extract colour, shape and texture details from flowers. SVM and MLP based models produced recognition accuracies ranging from 79.29 to 97.86% in the research with ten chrysanthemum cultivars, ten flower hues and five floral forms. In chrysanthemum and other decorative crops, these results demonstrate the promise of AI-driven picture recognition for quick cultivar identification, phenotypic characterisation, breeding, crop management and automated grading (Nguyen *et al*., 2024).

Deep learning shows great promise for the automatic recognition of chrysanthemum cultivars overcoming challenges due to complex inflorescence structures, diverse floret types and large numbers of cultivars. The top-

5 recognition rates of the VGG16- and ResNet50-based models trained on 14,000 images of 103 cultivars were over 98%, and the evaluation with images from different years showed good generalisation with rates over 78%. Further analysis using Grad-CAM and feature clustering suggest that inflorescence edges, disc florets, flower colour and inflorescence shape were important in discriminating between cultivars. The results of this study show the potential of deep learning for fast, accurate and scalable identification of cultivars in ornamental horticulture (Liu *et al*., 2019).

Automated recognition of flower species and cultivars has shown great potential with convolutional neural networks (CNNs), especially where visual diversity makes manual identification difficult. A CNN based image classification system was developed to distinguish different rose types using RGB images in roses and the classification accuracy was 96.33%. The model has employed multiple convolutional and pooling layers along with dropout to enhance feature extraction and classification performance. These AI based approaches help in automated flower identification, sorting and marketing and at the same time reduce the dependency on specialised botanical knowledge and manual classification (Anjani *et al*., 2021).

Automated flower identification using deep learning-based object detection has been successfully used especially for discriminating among visually similar species and cultivars. A framework was created to detect, localise and classify flowers by using Faster R-CNN and SSD with pretrained architectures like ResNet, Inception and MobileNet. The transfer-learning based Faster R-CNN achieved mAP values ranging from 83.3% to 91.3% based on the number of region proposals using 2,000 images of ten flower classes. The method shows the ability of deep learning to automatically recognise, locate and classify flowers which will help in the rapid identification and extraction of phenotypic information in ornamental horticulture (Abbas *et al*., 2022).

Recent advances in self-supervised deep learning have improved automated flower recognition by improving feature learning from large collections of unlabelled images. We obtained 99.6% classification accuracy on the Oxford 102 Flowers dataset with a masked autoencoder-based approach, showing the strong ability to learn robust and discriminative flower features. The pretrained model also provided flower detection with a mean average precision (mAP) of 71.3%. Such approaches open up potential for automated species identification, flower detection, biodiversity assessment, dataset annotation and educational applications while alleviating dependence on manually labelled training data (Li *et al*., 2024a).

As a promising method for the real-time detection of flowers and crop monitoring under field conditions, UAV imagery combined with AI based object detection is getting popular. Several CNN-based detectors namely YOLO, Faster R-CNN, SSD and RT-DETR were trained and tested with field acquired and augmented images in marigold. The highest performance was obtained with a YOLOv2 model with a DarkNet-53 backbone reaching 98.8% mAP and 97.9% F1 score. Modern models, such as YOLOv11, YOLOv12 and RT-DETR, also showed high detection accuracy. The study indicates that traditional CNN architectures can provide highly accurate and computationally affordable flower detection with appropriate modifications, facilitating UAV-based crop monitoring, automated phenotyping and precision floriculture (Vilcapoma *et al*., 2025). Attention-based networks trained with multiple loss terms have also been proposed to sharpen flower image classification (Zhang *et al*., 2021), although evaluation on large commercially realistic cultivar sets is still uncommon.

2.2 Automated plant phenotyping

A systematic study on the application of CNN based deep learning for automatic prediction of ornamental flowers phenotypic traits in commercially important rose and gerbera varieties in Smart Agricultural Technology has been conducted. Prediction accuracy varied between 35% and 99% for traits with greater accuracy for traits with more distinct visual characteristics such as petal colour and bloom stage and lower accuracy for more subtle traits such as vase life potential. The study clearly established computer vision and deep learning as a potential alternative to the existing labour-intensive manual cataloguing method for variety registration for plant breeders' rights protection (Afonso *et al*., 2024).

Deep learning techniques are now allowing for the quick and objective determination of morphological characteristics in ornamental crops. In the case of chrysanthemum, light-weight deep learning models have been created to automatically classify different types of flowers, segment the ligulate and bisexual florets and estimate their diameters for a variety of cultivars. A classifier based on ShuffleNet V2 was able to achieve high accuracy while keeping low computational demands and fast inference times. Likewise, an optimised U-Net model offered accurate floral segmentation and the use of machine learning on geometric and texture features allowed for a detailed classification of floral features. These combined image-based methods can greatly overcome the drawbacks of manual phenotyping and enable fast, non-destructive, high-throughput evaluation of floral traits with possible uses in cultivar characterization, quality assessment and breeding programmes (Xu *et al*., 2025).

A method that uses machine learning to aid visual sensing provides a quick and non-destructive way of telling different plant materials apart according to their biochemical properties. For lily bulbs, a dual-channel fluorescent sensor array made up of nanogold clusters (AuNCs) and quantum dots (QDs) was created in order to distinguish bulbs that come from different geographical areas. Differences in the composition of amino acids and phenolic acids caused particular fluorescence responses by means of aggregation induced fluorescence enhancement and aggregation-caused quenching, resulting in distinct colour patterns. The spectral visual responses were then analysed with a Random Forest (RF) model, this model achieving a prediction accuracy of 94.4% when identifying the origin of the bulbs. Combining portable visual sensing with machine learning shows promise for enabling fast,

objective and automated phenotypic characterization of plant materials on the basis of their biochemical signatures, with possible uses in cultivar authentication, quality assessment and traceability (Long *et al*., 2024).

2.3 Flower and bud detection

Deep learning methods are being used more and more to automate the recognition, grading and evaluation of cut flowers. In order to detect spray roses under conditions involving occlusion and varying stages of flowering, an improved version of the YOLOv5s model was created. This model included features for detecting small objects, used attention mechanisms and featured an enhanced WIoU loss function which improved both feature extraction and detection accuracy. For the 'Orange Bubbles' and 'Yellow Bubbles' varieties of spray roses, the improved model achieved a 10.2% increase in detection accuracy and a 20.0% increase in recall respectively and attained 95% detection accuracy when tested on randomly selected bouquet images at a confidence level of 0.8. These results show the promise of YOLO-based models for use in automated flower detection in assessing the flowering stage and in sorting and grading within the commercial floriculture industry (Li *et al*., 2024b).

Machine vision methods can be used as a non-destructive alternative to manual counting when grading cut flowers. For cut lilies, a combined approach that makes use of colour-space threshold segmentation, support vector machine (SVM) classification and ellipse fitting was developed in order to detect and count the buds even though the buds are similar in colour and are partly obscured by leaves and other buds. This technique achieved a counting accuracy of 81.2 per cent, with 91.4 per cent of the buds successfully fitted and the mean relative errors for the estimated bud dimensions stayed below 5 per cent. The time taken for the processing was about 2.37s per image showing the promise of computer vision for fast bud counting and for the automated grading and quality assessment of cut flowers (Li *et al*., 2023).

2.4 Growth and flowering prediction

AI-based image analysis and the use of UAVs for remote sensing are becoming more and more widely explored as a means of automatically monitoring flowering in commercial rose nurseries. In order to deal with the problems caused by the small size, clustering and partial occlusion of the blooms in UAV images, a multimodal framework combining supervised deep learning, unsupervised computer vision and large language models was developed. A YOLOv8m model that used a tiling approach with sliding window inference attained good performance in detecting blooms with a mAP@0.5 of 0.985 and a recall of 0.948, while a method for quantifying blooms based on RGB images without the need for annotations achieved 93.1% accuracy through the use of colour thresholding, morphological processing and contour analysis and it did not require any GPUs or training data. The bloom-count information was then processed using large language models that were locally deployed in order to produce management recommendations concerning labour allocation, irrigation, fertilizer application and harvesting schedules. The study shows the potential of combining AI-based bloom detection and quantitative monitoring with decision support systems for precise flowering management in rose production (Sundaravadivel *et al*., 2026).

Deep learning methods offer a promising way of identifying the flowering stages and deciding the right time for harvesting ornamental crops. For marigold, a Faster R-CNN model that had been fine-tuned using a ResNet50 backbone and data augmentation was created in order to detect and classify flowers in complicated field conditions. The dataset consisted of images taken in three marigold fields in Gujarat, India, under natural light and with different camera angles, heights and distances. The model was developed to enhance the detection of flowers and the classification of flowering stages, overcoming the drawbacks of subjective and manual evaluation. The approach shows the potential of deep learning for automated monitoring of flowering stages, determination of the harvest time and quality control in commercial floriculture (Patel, 2023).

2.5 Disease and pest detection

Deep learning methods are becoming an effective means of quickly and objectively detecting diseases in ornamental crops. For roses, an application called Spotibot has been developed which is available both on mobile devices and on the web to measure infections of Botrytis cinerea on the petals, thus aiding in the screening of different genotypes for disease resistance. The system used a coarse-to-fine segmentation approach, involving separate instance segmentation models that detected individual petals and Botrytis lesions, attaining F1-scores of 0.99 and 0.96 respectively. The application was able to automatically calculate the petal area, the lesion area, the lesion diameter and the lesion-to-petal ratio, with the objective measurements showing a strong agreement with those made by humans. Moreover, statistical analysis showed that there was better discrimination among rose genotypes when using the quantitative traits derived from the images than when using subjective scoring, showing the potential of deep learning for high throughput disease phenotyping and for resistance breeding in floricultural crops (Rustia *et al*., 2025).

Machine learning and image processing methods have shown promise in enabling the early and non-destructive detection of diseases in orchids, thus allowing for timely crop management and helping to reduce possible losses in production. In order to detect diseased orchid leaves, an image-based system was created which examined the colour features in the HSI, RGB and grayscale colour spaces. The leaf images were segmented into healthy and unhealthy areas using histogram analysis and green colour thresholding, after which the disease patterns were classified with the help of an artificial neural network (ANN) and deep learning techniques. The approach obtained 100% recognition accuracy on the training dataset and 90% on the testing dataset. This shows the potential of AI assisted image analysis for the early identification of diseases in orchids and its use in precision floriculture to improve crop monitoring and disease management (Li *et al*., 2019).

Image analysis of orchids, based on both deep learning and machine learning methods, has shown promise in the early and automated detection of viral diseases. In the case of *Phalaenopsis*, a diagnostic system was created by applying a colour space transformation and gamma correction during preprocessing, using U-Net to segment the leaves, carrying out connected component analysis to eliminate non-leaf areas and then employing a two-stage classification approach that combined Random Forest with an Inception based deep learning method. This system reached segmentation accuracy of 97.07% and a disease identification accuracy of 91.80%. When it came to visually similar infections such as Cymbidium mosaic virus (CymMV) and Odontoglossum ringspot virus (ORSV), the AI-based system obtained an accuracy of 84.2%, as opposed to 66.7% when relying on visual assessment. These results show the potential of AI assisted image diagnostics for enabling quick, cost effective and objective detection of disease in commercial orchid production (Tsai *et al*., 2022).

The use of deep learning for object detection is becoming more and more common as a means of quickly diagnosing diseases in rose farming at the field level. Traditional visual assessment of diseases is tedious and hard to scale up and models that have been developed under laboratory conditions usually show lower accuracy when they are applied in complicated field situations. In order to overcome these problems, a knowledge-distillation framework was created in which a high-capacity YOLOv12-L teacher model, which had been trained on laboratory images, passed on its feature representations to a lighter YOLOv12-N student model using field images. The model that had undergone distillation achieved an mAP@0.5 of 81.1% on the field test images, which is a 3.5% improvement on the baseline YOLOv12-N, even though it needed only 2.56 million parameters and 6.3 GFLOPs. The findings show that it is possible to improve lightweight models under cross domain conditions by transferring robust feature representations from a previously trained teacher without having to substantially increase their computational demands. Efficient deep learning approaches of this kind have the potential to enable real time detection of rose diseases and to be used on field equipment with limited resources, thus supporting precise disease monitoring in commercial floriculture (Liu *et al*., 2026).

Pest monitoring is more suitable for the technology currently available since the sensing environment can be controlled. Whiteflies and western flower thrips, both of which are important in the protected cultivation of ornamentals are small in size and occur in large numbers, thereby overcoming the limitations of simple detectors. (Li et al., 2021) a deep-learning pipeline for detecting small pests from images taken on sticky traps in agricultural greenhouses and (Wang et al., 2021) using larger-scale feature maps YOLOv4 was improved and additional residual units in order to achieve greater accuracy for the same task. Although neither of these studies involved ornamental crops, the trap image approach is independent of the type of crop; therefore, the methods can be directly applied to greenhouses growing gerbera, chrysanthemum and rose. In cases where pest images are limited, GAN based augmentation has been found to assist lightweight detectors in counting whiteflies (Karam *et al*., 2022).

2.6 Flower quality assessment

Image analysis based on artificial intelligence is a promising approach to the automated postharvest quality grading of cut flowers, in particular in the detection of physical damage that lowers their value. For cut roses, deep learning models were trained to detect petal damage and bent flower heads. A compact version of the YOLOv5 model was used for petal damage detection with an average precision of 92.1%. Moreover, an optimized HRNet model was employed for flower head detection and bent head localization. The combined system achieved a 97.9% accuracy for damage detection while keeping the system complexity low. Such results point to a promising use of lightweight deep learning models in rapid and objective detection of physical damage in cut flowers that does not require contact with the object (Chen *et al*., 2025).

Thirdly, machine vision and deep learning-based image processing is able to improve the accuracy of quality evaluation for potted ornamental plants by eliminating the disadvantages from visual occlusion at image acquisition. For potted Anthurium, plant image based automated grading relies on the measurement of number and size of spathes through the image capture. Nevertheless, a series of spathes occluded and some incomplete image regions could result in the measurement accuracy down because of limited angles of camera. To address this problem, a multi-scale fusion Recurrent Feature Reasoning network was proposed to reconstruct the incomplete spathe areas from the multiple-scale feature fusion, multi-layer feature reasoning and structure-aware reconstruction method, which effectively recovered the details of fine structure in the potentially large missing region, especially in the near-complete, semi-incomplete and semi-incomplete images. Experiments demonstrated that the proposed method outperformed the traditional image-completion models on the image reconstruction of varied incomplete image levels. This study highlights the potential of deep learning-assisted image reconstruction in non-destructive flower quality detection and automated grading of ornamental plants (Wei *et al*., 2023).

On the other hand, jasmine flowers for tea and perfumery must be harvested at specific stages of development. A trained YOLOv7 is used to classify small, half-open, open, fully-opened and withered buds with a mAP of 0.948 and per-stage accuracy of 86.4% to 93.9%. Indian jasmine, which is harvested by hand, has the same challenge of precise timing (Zhou *et al*., 2024).

2.7 AI in Flower harvesting

Computing vision combined with robotics has shown promise for automation of flower harvesting systems. In *Gerbera jamesonii*, a stereo-camera system with near infrared illumination was used for identification of flower pedicels and triangulation and image segmentation was used to produce three-dimensional plant models. This spatial information was fused with a six-axis robotic system with a pneumatic cutter gripper for automated pedicel

harvesting. All pedicels were identified in at least one image position for 97% of plants and a total harvesting rate of 80% was achieved. The overall harvesting efficiency was observed to decline with increased numbers of pedicels per plant so improvements would be required for perception and path planning algorithms. Vision systems such as this can pave the way for automated accurate and non-destructive flower harvesting in the future (Rath *et al*., 2009).

Robotic harvesting is under development to minimize labour needed for commercial flower production. A passive end effector for gerbera was developed based on plant architecture, with precise measurement of plant spatial characteristics for accurate flower positioning and cutting. The end-effector is combined with highspeed sensing and image processing for plant feature detection and end-effector targeting and then evaluated in commercial greenhouse environment, demonstrating 78% overall success rate with a low collision rate and sufficient positional accuracy and cut quality. These results highlight the promise of end effector design based on AI enabled sensing and robotic sensing to enable automation of commercial flower production (Sytsma *et al*., 2025).

Synthetic data generation, deep learning and computer vision show great potential in automation of flower detection and localization at varying field conditions. For example, in Calendula a photogrammetry-based flower field simulator was used to generate synthetic images to train a deep neural network for sim-to-real transfer with synthetic data alone without the need for real images to train the detection model. The detector achieved an F1 score of 86% when tested on real images and a 3D flower localization system with a stereo vision setup was able to localize flowers with an average height estimation error of 6.9 to 5.1mm. This highlights the capability of synthetic data sets to lower the cost and effort of large-scale image collection in agriculture and to enable accurate vision-based localization for robotic flower harvesting in the wild (Vierbergen *et al*., 2023).

Artificial intelligence (AI) aided computer vision is showing great potential for automating the harvesting of edible flowers in scenarios where hand picking is labour intensive. A vision-based robotic harvesting framework was proposed by combining YOLOv5 for 2D flower detection, the Segment Anything Model (SAM) for extracting relevant features of 3D point clouds and spatial localisation of flowers, implementing flower pose estimation and introducing a regression-based approach to learn the relationship between flower diameter and plucking point for flower plucking point prediction. The framework showed accurate 2D flower detection and promising performance in 3D flower localisation, flower pose estimation and plucking point estimation for different edible flower species and cultivars. This study illustrated the potential of deep learning, 3D computer vision and robotics for precise and flexible automated flower harvesting (Taddei *et al*., 2024).

Segmentation based on deep learning can be used to improve the accuracy of robotic flower harvesting by precisely locating the suitable picking point of the flower. In marigold, a lightweight SCS-YOLO-Seg model was proposed to overcome the drawbacks of complex background and the different orientation of flowers. The model was based on YOLOv8n-seg, by introducing a lightweight Star Net backbone network, a C2f-Star feature extractor and a dual-path Seg-Marigold head and the size of the model, the number of parameters and computation were reduced, while segmentation accuracy was achieved. After the extraction of flower masks, elliptical fitting was applied to accurately locate the optimal picking point by combining the information of stem skeleton and fitting ellipse. The model's accuracy of a single image for identification of the optimal picking point reached 93.36%, and the average speed for identification of a single image was 28.66ms. The use of lightweight deep learning-based segmentation has the potential for real-time flower localization and robotic harvesting in difficult conditions such as medical applications (Ma *et al*., 2025).

Computer vision-based stem analysis can also be used to support the robotic harvesting of cut roses through the determination of the correct cutting position. In greenhouse grown roses, the point of cut is determined by the thickness of the stem and the position of the stem eyes, but direct recognition of stem eyes through image processing can be difficult in the conditions of a practical harvesting environment. Therefore, an alternative method was developed using the correlation of the size of the diameter of the stem with the cutting length measured from the branch point. Based on measurements of 239 cut stems of harvested roses, the relationship between the size of stem diameter and the length of the cut was found to be linear. Based on these measurements a vision-based algorithm, comprising of detection of branch point and measurement of the stem thickness and the prediction of the length of cut was developed to define the position of cut for autonomous harvesting of roses. The detection algorithm for identifying branch points worked quite well in the absence of overlapped stems and was able to localize the branch point with enough precision for performing the robotic cut (Gürel *et al*., 2016).

Robotic plant handling is being investigated to deal with labour and ergonomics problems faced in commercial rose harvesting, especially in low light or dark conditions. A robotic system for picking flowers was established using a night vision camera to detect the flower and a processing system based on a Raspberry Pi to identify the rose based on its colour and visual appearance. The design of the prototype was aimed at minimising the risk of the manual operation such as thorn pricks and back pains from bending, while allowing the flowers to be picked at night. Combining machine vision with robotic control lays the foundation for flower detection and harvesting automation to achieve efficiency benefits, labour reduction and no limit to working hours (Subramanian *et al*., 2022).

2.8 Grading and sorting of flowers

Machine vision can also facilitate rapid and non-destructive automated grading of flowers according to their quality attributes. An intelligent grading system was successfully developed and applied for Imperial chrysanthemum flowers where colour, shape, integrity and flower diameter were used as characteristics to classify

the flowers into five quality grades. Image preprocessing, RGB-based colour feature extraction, image segmentation and edge detection were combined in order to extract floral properties and classify flowers based on their grade. The system had an overall classification accuracy of 97.6%, and was more than five times faster than manual grading. This research indicated that computer vision can be used to facilitate fast, accurate and reliable automated flower grading in the ornamental flowers industry (Zhang *et al*., 2022).

AI-based multi-task vision systems are being designed to bring rapid, real-time, objective and automated grading of flowers to the market. An end-to-end multitask multi-dimension YOLO (MTMD-YOLO) framework combining depth as well as RGB images was developed to simultaneously localize, classify and grade flowers based on maturity. The integration of depth and multi-task learning resulted in a higher grading accuracy while improvements to the feature fusion layer, detection heads and non-maximum suppression increased the computational efficiency of the network. On an embedded Jetson Orin NX platform, the system was able to achieve a mAP of 98.19% for classification and 97.81% for grading in real time (37 FPS). Further, their paper discusses the technological feasibility of systems such as this for real-time, automated fruit and flower grading, as well as determination of the optimal harvest period and integration with automated flower picker systems (Duan *et al*., 2024).

Objective and automated grading of flowers in the case of flower grading, deep learning-based computer vision can replace subjective manual grading with a more precise automatic classification based on image classification. For fresh cut roses, researchers developed an improved YOLOv8s model for detecting unopened inner petals and classifying the five classes of flower openness including the four developmental stages and the deformity and optimized the original backbone by introducing a lightweight MobileNetV3 structure. In addition, an Efficient Multi-scale Attention (EMA) module was integrated into the model, the Wise-IoU loss function was used to accelerate the model convergence and the model was combined with an automatic grading machine. The accuracy of this system was 6.5-12.6 % in each grade compared to the manual method, indicating the feasibility of using lightweight deep learning models for real-time automated grading of fresh-cut roses based on flower openness (Lai *et al*., 2025).

Application of deep learning object detection for fresh cut flowers grading Deep learning-based object detection has been widely used for gradation of fresh-cut flowers to increase the efficiency and accuracy. For example, the Garden Rose dataset was used to classify cut roses flower head by four grades based on flower colour, size and freshness, adopting a lightweight model called Flower-YOLOv8s with speed and accuracy for classifying roses to grade levels. DWConv and optimized spatial attention module (SAM) were introduced into the backbone network of YOLOv8s to capture the more important feature information while accounting for the complexity of computational performance. Results showed that the accuracy, recall and mAP of the improved model were 97.4%, 95.4% and 0.7% higher than the baseline YOLOv8s model. The number of model parameters was decreased by 2.26 million and the inference speed was increased from 15.6 to 5.7ms. A comparison of the proposed model with several other convolutional object detection methods including Fast R-CNN, Faster R-CNN, SSD, YOLOv3 and YOLOv5s was also undertaken to validate the robustness of the model for rose grading. The study indicates the effectiveness of lightweight deep learning object detection approach for graded, rapid, objective and real-time grading and sorting of fresh-cut flowers (Zhang *et al*., 2024b).

2.9 Postharvest management and vase life prediction

AI-driven adaptive control can also be employed to optimize postharvest processing and reduce quality losses in ornamental flowers. An intelligent control system using deep learning was designed for hot-air drying of chrysanthemum by coupling image-based quality evaluation with real-time process control. A Spatial Interaction Aware Segmentation network was established to extract the features from the appearance of flower images accurately and then a Temporal Feature Enhanced LSTM model was proposed for predicting the quality change trend of flowers during drying with high accuracy ($R > 0.997$). Based on the quality prediction, the drying temperature and air velocity were controlled alternately every 10 min interval. The image-guided intelligent control system based on deep learning reduced the processing time and energy consumption by 36.73% compared with the traditional process with constant parameters and significantly enhanced colour retention, shrinkage and phenolic content retention of the dired flower quality (Xu *et al*., 2026).

Potential use of machine learning for predicting cut flower vase life based on pre-harvest data Preharvest morphophysiological traits have great potential for use as AI-based predictors of vase life in floriculture. For example, vase life in lisianthus was cultivar-dependent and differed across the cultivation system, salicylic acid concentration and treatment stage. Principal component analysis revealed correlations between vase life and dry weight, SPAD value, magnesium content and flowering time, with dry weight identified as the most important variable for estimating vase life. A machine learning-based automated model used these pre-harvest biomass-related traits to predict postharvest vase life successfully. This methodology could facilitate early vase-life predictions for optimizing postharvest quality and storage and assist in cultivar screening and industry standardization (Kwon *et al*., 2024).

Combining hyperspectral sensing (HSI) with deep learning offers a non-destructive strategy for early quality evaluation and vase-life prediction of cut flowers. A study employed HSI to monitor the physiological decline (gray mold disease caused by B. cinerea, and vase-life) of cut roses. The spectral signatures revealed a spectral range of 470 - 680 nm and 700 - 900 nm and were highly correlated with gray mold disease and flowers' wilt or vase-life, respectively. A YOLOv5-based model built using 3000 HSI images effectively graded the cut roses for

vase-life and detected gray mold growth. The prediction model was highly effective in vase-life prediction of All for Love (R = 0.86) and White Beauty (R = 0.83). These outcomes underscored the potential of combining hyperspectral sensing with deep learning to enable rapid, non-contact detection of postharvest diseases and early prediction of cut flower longevity (Kim *et al*., 2024).

Artificial intelligence (AI)-based systems are also being developed to automate vase-life evaluation in cut flowers. In cut roses, a vase-life monitor system (VMS) based on image capturing using the camera system and deep-learning object detection technique YOLOv8 was developed to monitor continuously the variation in the levels of flower opening, fresh weight, water uptake and gray mold infection. The measurements obtained using the VMS were consistent with those obtained by standard observational methods and the YOLOv8 system achieved an object detection accuracy of 90% with a consistent performance based on mAP@0.5. Regression analysis revealed a strong correlation between measures of vase life using the VMS and those using standard observations. The combined use of microscopic imaging systems with the regular monitoring enabled early detection of physiological changes and development of gray mold, suggesting that automated AI systems hold promise for rapid, precise and non-invasive evaluation of postharvest quality parameters, such as vase life and disease resistance traits of flowers for cultivar improvement and breeding. (Ham *et al*., 2025).

Postharvest Quality Monitoring and Vase Life Prediction Using Hyperspectral Imaging in Cut Roses Non-destructive postharvest quality monitoring and vase life prediction using HSI combined with deep learning in cut roses, the effects of illumination sources on spectral image quality, flower temperature and vase life was compared in the two cultivars 'All For Love' and 'White Beauty'. While the data showed that halogen illumination yielded spectral images of better quality (from 480-900 nm) and the highest YOLOv11x detection performance (mAP@0.5 of 85% and 83% in 'All For Love' and 'White Beauty' respectively), it resulted in high flower temperature and water loss rate and thus decreased vase life; a negative correlation was established between temperature and vase life. Fluorescent and LED light did not exhibit significantly different effects on temperature and vase life, but spectral interference during deep learning detection was observed. Overall, the study indicated that careful selection of illumination source is crucial in HSI-based deep learning applications and both halogen lighting for further spectral analysis, as well as LED lighting for routine operation are recommended (Kim *et al*., 2026).

3. Applications of AI and Deep learning in Landscaping

3.1 AI assisted landscape design

Moreover, AI is increasingly integrated into landscape planning and design to address sustainable and environmentally responsive decision-making. The deep learning and the application of DNNs in combination with landscape architecture, has created human-centred intelligent design environments to allow users to create and modify the neural network models with a VR-based interface. These models can then be automatically translated into computational modules and tested in real-time for iterative refinement. AI-assisted solutions can include environmental factors such as plant selection, carbon dioxide mitigation and air quality improvement in landscape planning and landscape design. The synergy of human-centred AI, Web 4.0 and deep learning, therefore, can facilitate adaptive, data-driven and environmentally conscious landscape design while improving the efficiency of landscape design decision-making processes (Chen, 2023).

AI for landscape planning and design Visualization via AI-enabled tools can support the landscape design process and communicate a landscape vision in Landscape Architecture (AL/WA 2025). Using text-to-image diffusion models (Stable Diffusion) and tools such as Control Net and LookXAI, the visualization of landscape design has been examined as one of the studies in the Landscape AI tool competition (blinx@china 2024) and compared to traditional human rendering. Assessment criteria (e.g. Geometric accuracy, representation of materials and condition of planting) with quantitative measures (cosine similarity and structural similarity index) indicated that these AI tools could interpret the landscape spatial arrangement, diverse vegetation conditions and design context, although issues such as artifacts of materials and the possible bias in model output are critical limitations. Hybrid workflows between traditional workflows and AI applications are promising for visualisation and iterative design development with consistency of human artistic and biophysical decisions (Ashari *et al*., 2025).

Augmenting Landscape Visualization via AI Driven Technologies A VR-based landscape design method integrating 3D laser scanning, image reorganization, adversarial generative networks and texture mapping was proposed to assist in the reconstruction and visualization of urban architectural landscapes. The method facilitated the automated generation of landscape scenes of realistic three-dimensional objects with enhanced rendering efficiency and visual impact. The computer-generated landscape images could be generated up to 90 per cent faster than traditional design software including SketchUp and 3D Studio Max and the image quality can also be higher than those achieved with the traditional technology (He *et al*., 2025).

3.2 AI assisted plant selection

AI and machine learning are being used to identify the most suitable plant species for sustainable urban landscaping and indoor gardening efforts AI-based intelligent plant recommendation system has been developed based on real-time environmental parameters such as temperature, relative humidity, soil moisture etc. captured by a sensor network. Environment Sensor Based Plant Advisory System used an ML-based Random Forest classifier to detect environmental parameters and match them with a plant database to recommend suitable species

for growth environment. It was reported that this approach can enhance plant establishment and save resources by providing environment specific plant selection (Patil *et al*., 2025).

3.3 Intelligent landscape management

A machine learning algorithm was constructed to prioritise the development of green space in Tehran based on the integration of socioeconomic, environmental and ecological sensitivity indices from Google Earth Engine, air pollution monitoring networks and modelling with meteorological algorithms. Random Forest was the classifier that performed best, with over 94% overall accuracy, recall and F1-scores, when compared to other classifiers (XGBoost, Light GBM, Random Forest and Extra Trees) in binary classification of green space presence. There was a four-way tie between the other classifiers. The feature importance analysis indicated nighttime land surface temperature and the various sensitivity indices as the strongest predictors of green space inadequacy, providing greening strategists with data-rich prioritisation maps to direct planting and greening action (Ganjirad *et al*., 2025). The management of urban green space management has been examined using an integrated GIS approach incorporating the methods of analytic hierarchy process (AHP), machine learning, weighted linear combination and multi-criteria decision-making techniques to appraise the suitability of green space in the Konak district of Turkey. The combination of participatory GIS model and the application of AI in spatial analysis (similar in some projects in Liverpool and in Amsterdam), has thus bridged the gap between planning optimisation of data and policy makers (users), thus demonstrating the ability of the tools to not only allow technical planning decisions but also promote democratic participation (Başeğmez *et al*., 2025).

4. Challenges and research gaps

4.1 Data scarcity and cultivar diversity

All of the deep learning models examined in this article rely on a labelled image dataset, and it is in this area that floriculture research is at its weakest. While major food crops benefit from large benchmark datasets that have been accumulated over more than ten years, there is no similar resource available for ornamental crops, which is why almost each of the studies reviewed here had to create and label its own images from beginning to end. The problem is further exacerbated by the great variety of the materials involved: horticulture as a whole encompasses more than 6,000 recognised ornamental cultivars and a model trained to tell apart a small number of chrysanthemum or rose cultivars therefore provides little help for the thousands of other cultivars that a commercial grower or breeder may need to identify (Yang *et al*., 2021). Since annotated datasets in ornamental horticulture are still dispersed among individual laboratories and not collected in shared repositories, it has become much more difficult than it should be to compare the results of different studies or to build on earlier work (Zhang *et al*., 2025).

4.2 Model generalisation and field deployment

A model which does well on the images used during its training often does much worse when it is put into use under different lighting conditions, at a different time of year or on a different batch of cultivars and this is also true in the case of floriculture. Several of the studies mentioned earlier in this review note a significant decrease in accuracy when a model that was trained in one season or on one group of cultivars is tested on images taken later on, since a flower's appearance varies with its stage of development, the amount of illumination, and even the angle at which it is photographed. The effect of petals, leaves or adjacent flowers overlapping the flower, complicated field or greenhouse backgrounds and the variation in natural light all cause detection accuracy to be lower than that achieved under the carefully controlled conditions usually employed when models are first validated (Zhang *et al*., 2025). The difficulty of overcoming the difference between performance in the laboratory and reliable field performance is still one of the main barriers to the commercial use of AI in both floriculture and landscaping.

4.3 Computational and economic constraints

In most parts of the world the floriculture industry is run more by small and medium-sized nurseries and cut-flower farms than by large, capital-intensive operations which are in a better position to bear the costs of high-performance computing, specialised cameras, robotic end-effectors and the technical personnel required to look after them. Even if a deep learning model works well, turning it into a practical tool such as an embedded system for use on a grading line, a handheld device for a field scout or a robotic harvester adds considerable hardware and integration costs on top of the cost of developing the model itself (Chaudhary et al., 2025). Because of this economic situation, many of the more advanced systems described in earlier sections of this paper, even though they have shown impressive accuracy, are still limited to research environments and have not yet been tested on the scale and at the cost that an average commercial grower could reasonably afford (Mahmud *et al*., 2023).

4.4 Interpretability, standardisation and trust

Deep learning models are popular among the experts, but often criticised as a "black box" that gives a prediction with no explanation for how that conclusion was reached (Krizhevsky *et al*., 2017). This criticism applies equally to the world of floriculture as any other sector using the technology. Growers need to be convinced that a system is worth relying on if it indicates a flower is diseased, mis-graded or ready for harvest and they need to know the reasons behind its decision, but only a small proportion of published research can deliver this because there is no standardised evaluation technique or performance metric to compare all the different studies (Caballero-Ramirez

et al., 2023). To gain the trust of growers, breeders and extension workers there is a need for models that are not only more accurate but more transparent too.

4.5 Handling delicate, high-value biological material

Robotic harvest and handling show another issue that applies much more to floriculture, as opposed to standard-crop production: the material being handled is the product itself, meaning that any damage in detection, grasping and cutting reduces the value of the end product. The earlier robotic harvesting systems, until now, tend to achieve success rates of 78 to 80 percent even under optimised, well-lit greenhouse conditions, and performance can only go south as the number of flowers or pedicels (small stems that hold single flowers) per plant increases, with the difficulty of detecting and manipulating into position among tightly packed, flexible, easily bruised stems and delicate petals (Sytsma *et al*., 2025). Giving next-generation flower handling comparable success rates to prototype prototypes means developing perception, path-planning and gripper designs that go way beyond retraining detection models on more flower images.

5. Future perspectives

5.1 Multimodal and generative AI for decision support

Future floriculture applications are, however, expected to be more complex, expanding from single-purpose classifiers and detectors to multi-modal pipelines that can contribute to an actual management decision. A forerunner of this, already described in this review, was a multimodal pipeline that, combining supervised deep learning for flower count detection with an unsupervised flower counting method and a locally deployed large language model translating counts into recommendations for labour planning, irrigation and harvest timing in a commercial rose nursery (Sundaravadivel *et al*., 2026). The 'multimodal' nature of this pipeline combining computer vision with language models, sensor data and grower-facing dashboards has the potential to bring to a grower-results that can otherwise only be interpreted by an AI researcher and generative methods capable of creating convincing synthetic flower images may also help overcome the dataset scarcity noted earlier (Vierbergen *et al*., 2023).

5.2 Explainable and lightweight AI for field deployment

To give growers confidence in the automated grading, disease-detecting or harvesting decisions, models will need to have explanations for their decisions rather than simple labels and the techniques of explainable AI already being used elsewhere in agriculture are likely to be incorporated into floriculture over the next few years. At the same time, the difficulties of using AI in the field, outlined above, suggest that we will also see an evolving need for low power, high speed models that can be run on cheap embedded hardware inside the greenhouse or on a phone in a nursery, rather than on the other side of an internet connection; both the knowledge distillation approach and the lightweight segmentation algorithm outlined above have been demonstrated to achieve high levels of accuracy at low computational cost for rose disease detection and marigold picking point detection, respectively (Ma *et al*., 2025). As with transparency, the ability for models to be both accurate and fast is likely to become the main criteria for models in commercial applications.

5.3 Smart, IoT and digital-twin enabled floriculture and landscaping

Smart horticulture combining the internet of things, big data, the cloud and artificial intelligence across all the stages of the process, from breeding through to transport and sales has been put forward as a possible way of guiding the horticultural sector into the next three decades or so and that vision includes floriculture and landscaping (Zhang *et al*., 2024a). Today, networks of sensors can constantly log environmental variables such as temperature, humidity, soil moisture and light levels in a nursery or greenhouse, while recommendation engine software can advise the user on the best plant choices or the ideal environmental conditions; and automating and extending these sensed conditions into a digital-twin model of a designed landscape would allow landscape managers to test management plans before implementing them (Mahmud *et al*., 2023).

5.4 Robotics and soft-manipulation technologies

It seems safe to assume that robotic flower harvesting will be an active area of research for some years to come, since current success rates are still too low for widespread commercialization and efforts in the next decade are likely to focus as much on refining physical end-effectors as on honing the vision models that guide them. Soft, compliant end effectors designed expressly for beating around delicate stems and flowers without bruising them and better path-planning for plants with many pedicels or flowers at once, seem a natural progression from the pneumatic cutters and rigid grippers that were the subject of the studies reviewed earlier in this paper (Taddei *et al*., 2024). In fact, this work will both aid floriculture and landscaping, since the perception and manipulation tasks needed to pick a flower without damage are not far removed from those needed to prune, transplant or otherwise care for decorative plants in a managed landscape.

5.5 Data ecosystems, breeding integration and policy support

Much of the progress covered in this review has come from individual teams with their own privately collected datasets and the collaboration required to combine them into shared benchmark datasets has been noted as an underdeveloped area, even in the broader deep-learning for agriculture literature (Zhang *et al*., 2025). More coupling of plant breeding efforts and AI also presents promising opportunities: high-throughput phenotyping, by now a routine application of computer vision, could be more closely integrated with molecular marker assisted breeding and genomic selection to accelerate developing new cultivars ready for the market (Wani *et al*., 2023). However, none of these changes will happen without coordinated and targeted encouragement from journal

editors, funders and industry associations specific to floriculture and landscaping to translate a series of worthy individual projects into an established high benchmarking field of agricultural AI (Ferrante *et al*., 2023).

6. CONCLUSION

Artificial intelligence and deep learning have become a real working tool in almost every stage of the ornamental value chain, moving from a curiosity in floriculture and landscaping. The review has traced progress from cultivar identification and phenotyping, through disease and pest surveillance, to growth and flowering prediction, harvesting, grading and postharvest handling and on to landscape design, plant selection and green-space management. Convolutional neural networks, transfer-learning frameworks and more recently vision transformers and multimodal systems that integrate computer vision and large language models have repeatedly matched or exceeded the accuracy of experienced human graders and taxonomists, often while working many times faster and without the fatigue or subjectivity associated with manual inspection. Still, these applications are not uniform in their maturity, by any means. Tasks based on static image classification including cultivar recognition, quality grading and disease scoring have now moved well beyond proof of concept, with a number of systems validated on commercial scale image sets and in a few cases deployed in conjunction with automated grading machinery. It's a different story with robotic harvesting and the handling of whole, living plant material. Even the more sophisticated end-effectors and vision-guided cutting systems discussed here hit a ceiling of about 78-80% success, a level that shows how unforgiving flowers and stems are to grasp and manipulate compared to the produce these robots were initially designed for. Somewhere in between are landscape-scale applications. Generative and GIS-integrated tools can now produce usable design options and green-space prioritization maps, but mostly as decision aids rather than autonomous planners. All these applications face a small number of cross-cutting challenges that will determine how fast the remaining gap gets closed. Ornamental horticulture still lacks anything like the large, shared, annotated image datasets that have spurred progress in row-crop agriculture. Most of the studies summarized here trained and validated their models on data collected, labelled and often never released by a single research group.

This makes it difficult to judge how well any one method would transfer to the thousands of cultivars actually managed by a working nursery or breeding program and adds to the well-documented tendency of these models to lose accuracy when tested outside the season, lighting or camera angle used for training. Another constraint that's easy to overlook in a research setting is cost. Much of the hardware behind these systems, from hyperspectral cameras to six-axis robotic arms, is still out of reach for the small and medium-sized growers that make up most of the industry. And the "black-box" nature of deep learning continues to limit how far growers and breeders are willing to trust a system's output without some explanation as to how it was reached. None of these limitations appear to be insurmountable and the trajectory outlined in the last sections of this review toward multimodal, generative decision-support tools, lighter and more explainable models deployable on greenhouse-grade hardware, IoT-linked digital twins of nurseries and landscapes, and soft robotic manipulators purpose-built for delicate stems and petals provides a realistic pathway around most of them. Less certain is whether the field will organize itself to get there. Floriculture and landscaping have historically borrowed techniques developed for food crops and general computer vision, adapting them one study at a time, rather than establishing the common benchmarks, standardized evaluation metrics and cross-institutional datasets that allow separate research groups to build on each other's work.

This review represents a small step toward bringing together these two closely related but rarely compared industries in one place. The larger step, of coordinated investment from journals, funders and industry associations in the kind of shared infrastructure that other agricultural sectors already enjoy, will determine how soon these largely proven technologies become standard practice on the nursery floor and in the public park alike.

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