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Artificial intelligence in post-harvest management of cut flowers: Disease detection, quality assessment and vase-life prediction

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Abstract
Short post-harvest life of cut flowers is one of the problems in the floriculture industry that may affect the quality, value, transportation, and consumer satisfaction of products. Traditional post-harvest assessment is based on visual observation and manual measurement and may be inaccurate, time-consuming, and unable to detect the initial signs of deterioration of the physiological status of the flower. Artificial Intelligence (AI), including machine learning, deep learning, computer vision, and hyperspectral imaging provides interesting solutions to enhance post-harvest activities. This literature review discusses the possibility of creating the integrated AI-based tool for disease detection, grading, and prediction of the display life of cut flowers. The algorithm will combine the information on the images of flowers, their spectra, physiological parameters, and storage conditions to calculate the level of the risk of deterioration and the estimated display life of a flower. Hyperspectral imaging and deep learning have already been used in the researches on cut roses for detection of the grey mould and prediction of the display life. Camera-based assessment has allowed the automatic estimation of the stage of flower opening, water intake, and disease incidence. There are still some difficulties in creating the models for various flower species, cultivars, environmental conditions, and commercial chains.

Keywords: Artificial intelligence, Cut flowers, Computer vision, Disease detection, Deep learning, Quality assessment, Vase life, Post-harvest management

Introduction

Cut flowers are valuable commercial commodities used in bouquets, floral arrangements, celebrations, decoration, and events. The commercial value of the cut flowers is determined by their freshness, color, form, vigor, uniformity, and vase-life. However, cut flowers continue to be metabolically active after harvesting and gradually experience water loss, petal senescence, loss of turgor, discoloration, and microbial spoilage.
Losses might arise during grading, packaging, transport, storage, wholesale, and retail stages. There might be fungal infections, especially grey mould resulting from *Botrytis cinerea*, that affect the flowers' quality, or insufficient water or improper temperature causing early wilting.
Human-based quality appraisal is mainly based on the observations of the human being. While seasoned personnel may be able to spot any defects in flowers, early infection and physiological stress may go unnoticed. The use of artificial intelligence could provide us with a chance to shift from a subjective form of appraisal into a more objective, fast, and predictive one.

Major applications of artificial intelligence

AI-based disease detection

Post-harvest disease is an essential factor that leads to poor quality cut flowers. Grey mould is among those diseases that are significant in roses and other ornamental plants. This infection can occur during transportation due to humid conditions.
Machine vision algorithms, such as convolutional neural networks (CNNs), can
be used to examine the images of flowers for any lesions, browned petals, discolorations, and similar problems. Object detection systems can detect any defects on the image.
Hyperspectral imaging involves capturing reflected light from various wavelengths that include non-visible wavelengths. Reflectance changes could be linked to tissue injury, drought stress, and infections even when no visible symptoms are present. Studies have shown the use of hyperspectral imaging in combination with deep learning for detecting grey mould and predicting longevity in cut roses. Such techniques need to be considered as screening techniques unless the disease is positively identified.

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AI-based quality assessment and grading

Flower quality depends on color of petals, flower size, opening degree, stem height and straightness, leaves, and damage. Computer vision systems can use calibrated images to determine these features, and hence, minimize grading variation among human graders.

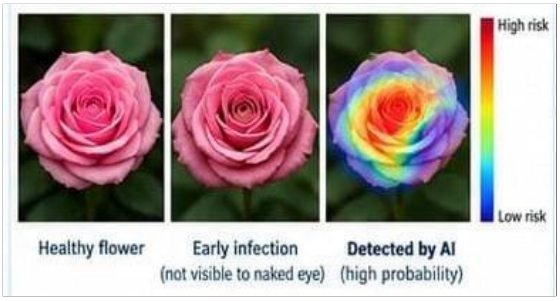


Figure 1. Example of AI-based disease detection (Grey Mould in Rose)

Application areas may include color analysis, flower opening stage classification, size and evenness analysis, stem quality assessment, and bruises,
damages to petals and leaves. Grading requirements should vary according to each plant type and destination. As an example, stem bending is essential for gerberas, whereas bloom opening and stem quality play crucial roles in rose assessment.

AI-based vase-life prediction

Vase life refers to the time during which a flower is fit for display under certain conditions. Some of the factors that affect vase life include species and cultivar, maturity at harvest, preharvest conditions, water uptake, temperature, humidity, ethylene sensitivity, microorganisms, and preservatives.



Figure 2. AI-based quality assessment (sample result)

Some machine learning techniques which include random forest, support vector regression, gradient boosting, and neural networks can be trained using observations made from vase-life studies. The models could predict the remaining display days or categorize the flowers into high-, medium-, and low-longevity. It is important that the predictions be validated for the intended species and handling methods.

Proposed integrated AI framework

The proposed review highlights a Flower Post-Harvest Intelligence System (FPHIS) that brings together disease risk assessment, quality grading, and vase life prediction for
a decision support system. This is different from other systems which assess one aspect because the system will be able to assess the post-harvest status of flowers.

Data acquisition

Images can be captured using a smartphone, digital camera, or stationary imaging system. Where available, hyperspectral images and environmental sensors can offer more information. Data can consist of flower appearance, variety, harvesting time, storage temperature, relative humidity, and handling history.

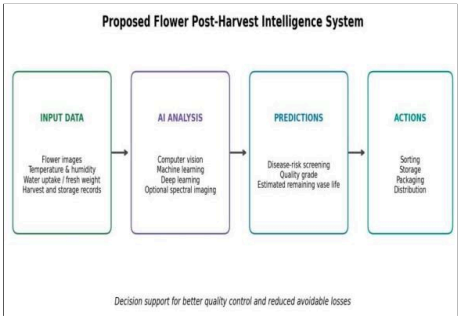


Figure 3. Conceptual framework integrating input data, AI analysis, predictions, and post-harvest decisions. This is a proposed framework, not a validated commercial system.

Disease-risk assessment

The trained model will detect visible signs of the problem and estimate the probability of disease. Information from spectral analysis can be used to determine whether early signs of stress can be detected.

Quality scoring

The computer vision will judge the appearance features like blooming time, color uniformity, petal deterioration, and stem health. The features and their significance will be determined based on species specific grading criteria.

Vase-life prediction and decision support

The prediction model will be based on calculations of risk of disease, quality factors, environmental data, and physiological factors for estimating the remaining life of the flower vase. These predictions may assist in directing high-quality flowers for better markets, indicating consignments for additional examination, and allocating short life flower vases for faster shipment.

Proposed research methodology

Selection of plant material

Reasons for choosing rose flowers to start with as a sample flower include the availability of post-harvest experiments using AI on the roses. Future flowers that can be considered in validating the model include gerbera, carnation, chrysanthemum, orchid, and bird of paradise.

Data collection

Flower characteristics should be monitored upon harvesting and at specific intervals throughout the evaluation process of vase-life duration. Flower observations can involve petal color and any defects, flower size and opening stage, stem bending, leaf status, fresh mass, relative fresh mass, water uptake, temperature, relative humidity, disease infection, and date and reason for the termination of vase-life.

Model development and validation

The data set should be labeled and split into training, validation, and independent test sets. The models that use CNN can either classify images or detect any defects;
meanwhile, the regression model can predict the vase life left.
Neither flowers nor batches used in the independent test set should occur in the training set. In case the pictures of one flower have been taken on different days, these pictures cannot be split into different sets.

Performance evaluation

Precision, recall, F1-score, and sensitivity can all be used to measure the effectiveness of disease detection.
Classification accuracy and the consistency of results with trained human graders can both be used to grade the quality. MAE, RMSE, and R^2 can all be used for evaluating vase life prediction. The AI system is to be compared to traditional methods and baseline statistics.

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Illustrative graph of vase-life prediction

Below is an example of a graph showing how the observed vase life of flowers can be compared to the predicted vase life using AI. These numbers are hypothetical and have been used only for illustrative purposes and are not actual results.

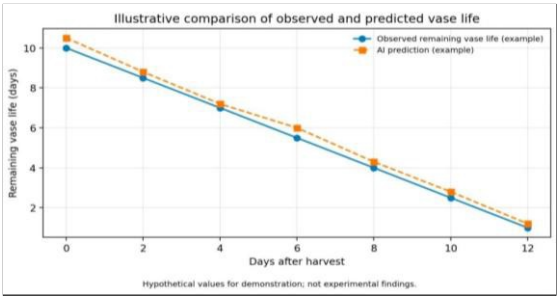


Figure 4. Hypothetical comparison of observed and AI-predicted remaining vase life.

A good model should give output that is near the actual value. The accuracy of the
prediction can be measured through MAE and RMSE. The performance should be evaluated on a separate testing set, preferably using different varieties and storage conditions.

Potential benefits for the floriculture industry

Reduction of post-harvest losses

Early disease-risk screening and physiological monitoring may help prevent unsuitable flowers from entering long-distance supply chains. This could reduce avoidable rejection and improve handling decisions.

Consistent quality grading

Automated assessment can reduce differences between graders and support more consistent quality classification across collection centers, packhouses, wholesalers, and retailers.

Improved transportation and inventory decisions

Predictions of vase-life will assist companies in deciding which flowers need to be prioritized based on their longevity.

Flowers that have higher estimated vase life can be shipped using longer shipping routes, whereas those flowers whose longevity is lower can be sent through shorter shipping routes.

Sustainable resource management

Monitoring might assist in reducing the waste of flowers and increase the usage of refrigeration, packaging, and post-harvest treatment. The improvements in sustainability will have to be seen in terms of reductions in waste, energy, and treatment.

Challenges and limitations

Small databases: It is still necessary to develop databases that would include different species, varieties, diseases, and storage conditions. Species differences: Different flowers have a different process of aging, ethylene sensitivity, water absorption ability, and acceptable appearance. An algorithm designed for roses will not work the same way for orchids and bird of paradise. Environment factors: Lighting, camera location, packaging, background, and storage conditions might affect results.

Detection of disease early on: There may be similarities in signs of disease from dehydration, physical injury, and infections. The spectral signature may not determine what causes these. Cost and availability: Hyperspectral technology and sensors could be costly for small-scale farmers. The use of smartphones for this may be cheaper but requires validation. Reliability and need for human involvement: Even high accuracy in the laboratory does not translate into commercial success.

Future research directions

Further research will need to design economical and species-specific AI tools. Databases with images, physiological and environmental information, as well as confirmed cases of the disease, will be useful in developing more universal models. Computer vision through smartphones can be an economical alternative for producers and collecting sites.

Multimodal models that integrate data from different types of information may be more effective in some cases.

AI explainability can aid scientists in finding out which features are more predictive of decline. Research also needs to be done to find out whether such an AI-driven decision-making process lowers losses and improves vase life.

Conclusion

Artificial intelligence presents an attractive option for post-harvest management of cut flowers by detecting risks of disease, objectively assessing flower quality, and predicting vase-life using imaging techniques such as hyperspectral imaging combined with deep learning algorithms. Studies of cut roses show the promise of artificial intelligence, but reliable implementation for different ornamental plant species needs more data and validation.

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