Advancement in Flower Recognition and Flower ClassificationTechniques

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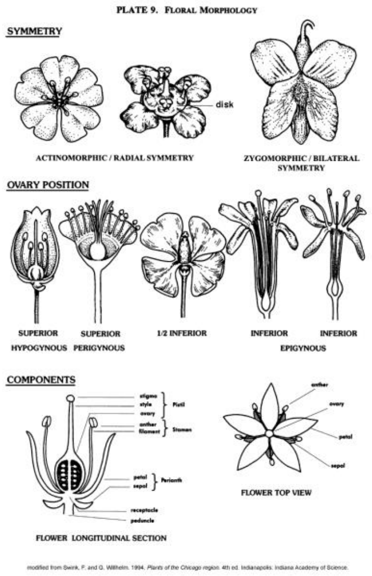
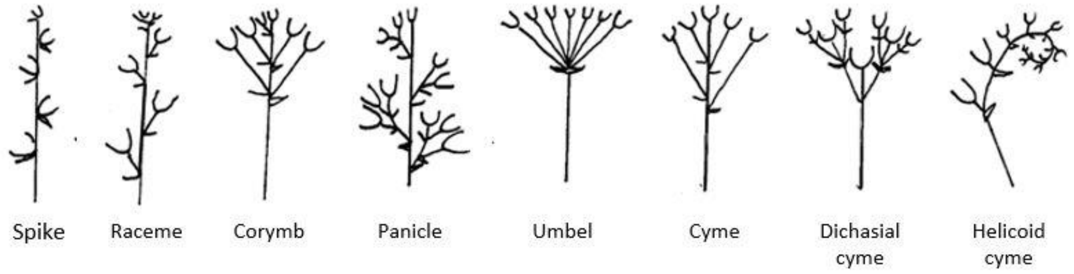
Introduction

- The world of flower recognition is undergoing a technology-driven revolution. In this review, we explore ten key studies that highlight how image processing and machine learning are reshaping the field of botany. These advancements have simplified flower identification and transformed phenological monitoring in floral environments.

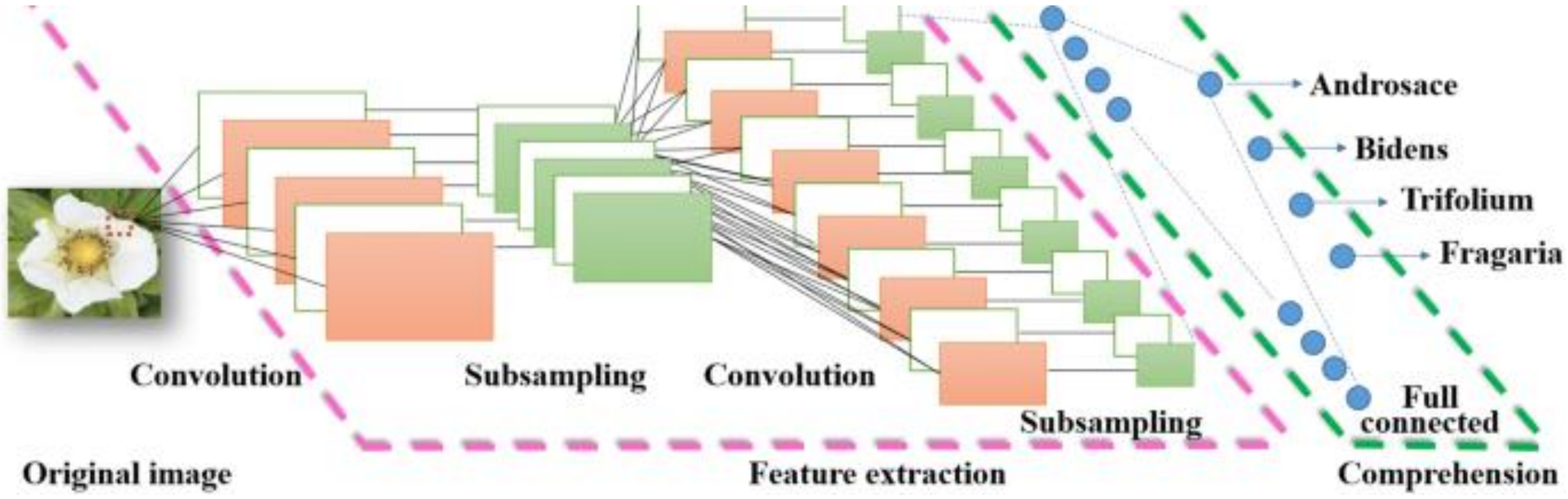
- This review delves into image processing, convolutional neural networks, deep learning, and transfer learning, all contributing to a profound shift in our understanding of flower recognition. The fusion of botany and technology is reshaping the landscape of floral studies and expanding our perspective on the natural world.

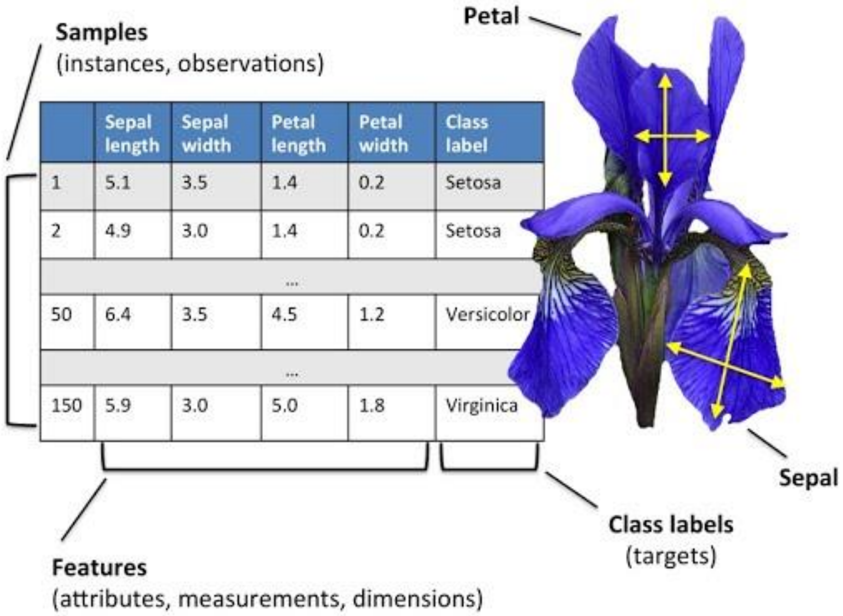




Methodology

- Multidimensional Approach: Advances in flower detection and classification involve deep learning, CNNs, machine learning, and visual processing.
- Innovative Approaches: Research articles over a decade have developed innovative methods combining these factors for improved flower classification based on shape, petal arrangement, and other features.
- Image Processing: Initial methodology relies on complex image processing techniques, including thresholding, edge detection, and color space conversions, to extract color, texture, and shape features.
- Flower Segmentation: Image processing techniques also facilitate flower segmentation, distinguishing the areas of interest and background, and improving feature extraction using morphological operations.
- CNNs for Deep Learning: CNNs are pivotal for flower recognition, learning intricate patterns, textures, and shapes specific to various flower species with convolutional layers.





	Sepal length	Sepal width	Petal length	Petal width	Class label
1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3.0	1.4	0.2	Setosa
			...		
50	6.4	3.5	4.5	1.2	Versicolor
			...		
150	5.9	3.0	5.0	1.8	Virginica

Transfer Learning: Pre-trained models like VGG-16, VGG-19, Inception-v3, and ResNet50 are fine-tuned for flower recognition, adapting them to focus on petal structures and morphological aspects unique to flowers.

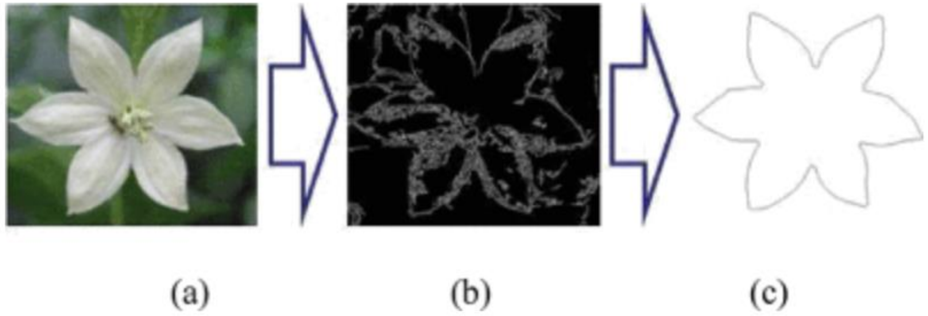
Machine Learning and Classification: Machine learning, using classifiers like SVM, KNN, and decision trees, maps feature vectors to flower categories.

Fusion Techniques: Some studies use fusion techniques to combine color, texture, and shape features for a holistic perspective on flower attributes.

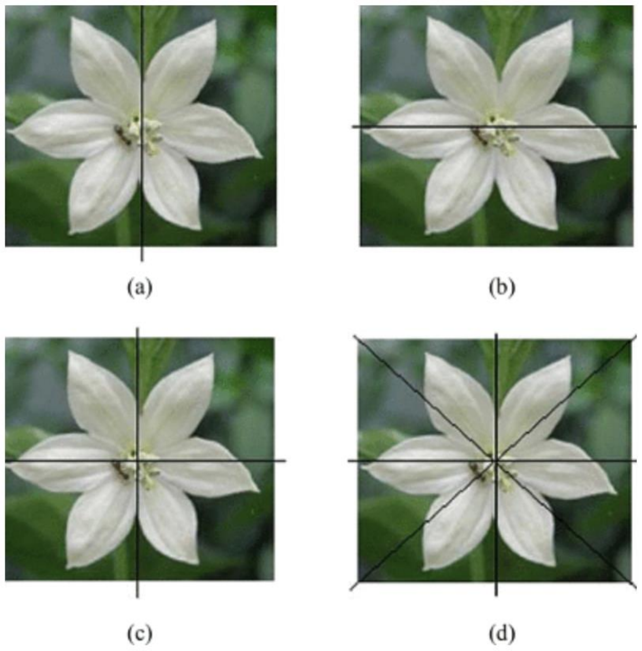
Cross-Validation and Dataset Preparation: Rigorous dataset preparation and cross-validation techniques ensure model accuracy and generalizability using datasets like the Oxford flowers dataset.

Validation and Testing: Validation and testing phases assess model accuracy and generalization on independent datasets.

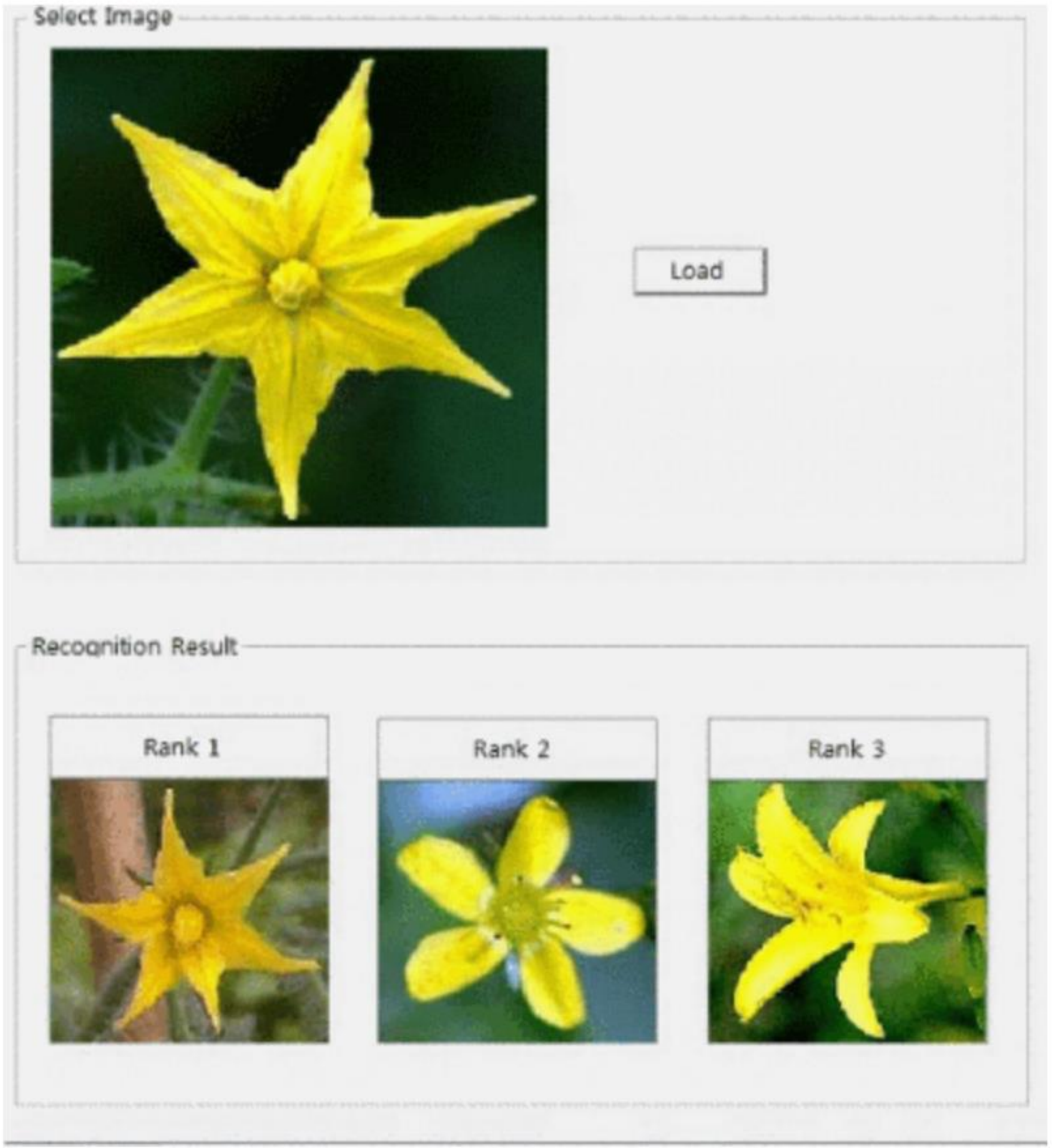
Evaluation Metrics: Metrics like accuracy, precision, recall, F1-score, and confusion matrices quantify model performance and areas of improvement.



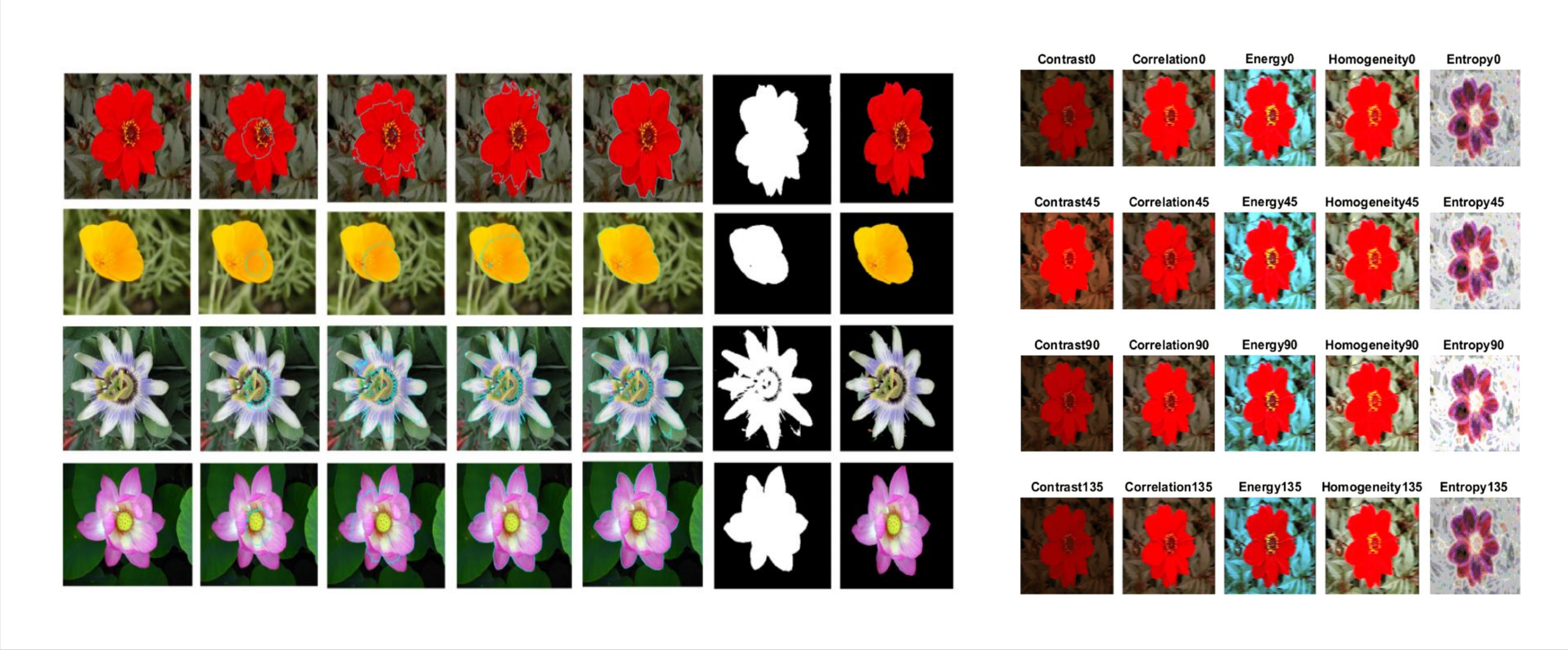
Edge-based contour detection process. (a) input,
(b) edge-based detection, (c) detected contour



An image (a) divided by 2 as vertically, (b) divided by 2
as horizontally, (c) divided by 4, and (d) divided by 8



Flower image segmentation with PCA fused colored covariance and gabor texture features based level sets



Applications

Accurate flower recognition holds pivotal roles across various domains:

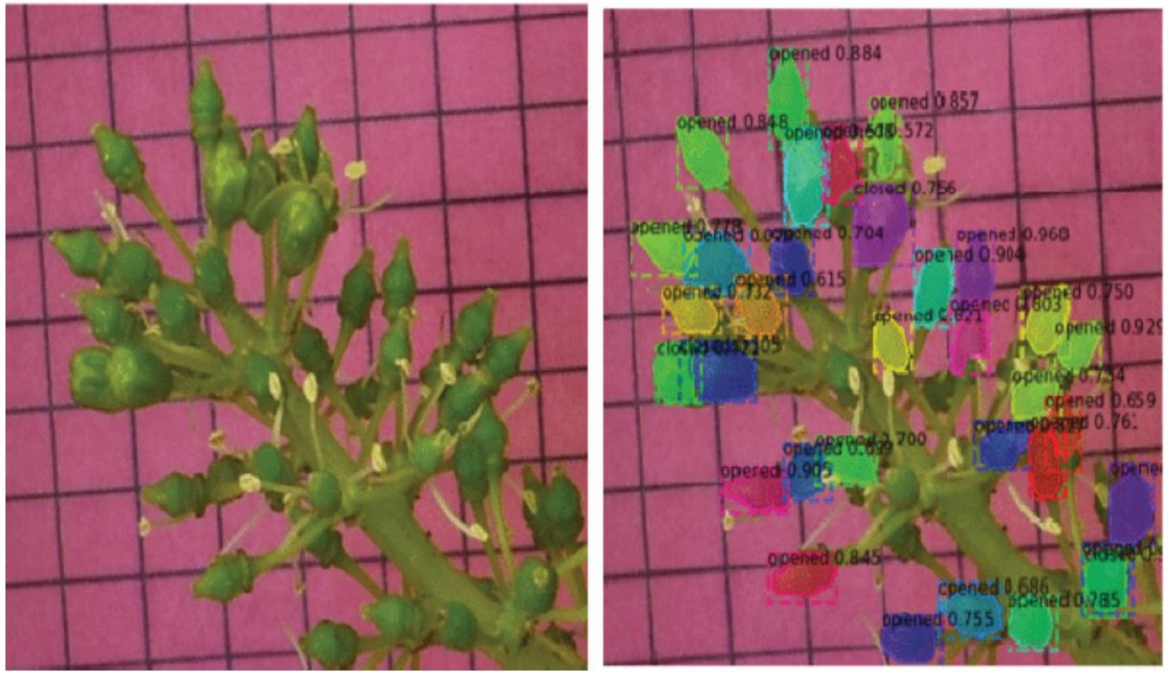
Biodiversity Conservation: Precise flower identification aids conservationists in quickly monitoring and preserving plant species, particularly endangered ones, contributing to overall biodiversity conservation.

Agriculture and Horticulture: Widely applied in farming and horticulture, flower recognition technologies assist in identifying and monitoring flower health, optimizing crop management, enhancing yield, and ensuring the vitality of ornamental plants.

Botanical and Ecological Research: In botanical studies, flower recognition proves indispensable for studying plant populations, understanding their distribution, and advancing ecological research. It contributes significantly to expanding knowledge in the field of botany.

Ecological Dynamics: Automation in flower recognition supports ecological research, enabling the seamless monitoring of floral ecosystems. This data is instrumental in comprehending plant interactions, pollinator behavior, and overall ecological dynamics, contributing to the conservation of natural ecosystems.

Phenology Studies: Flower recognition techniques play a crucial role in phenology studies, aiding researchers in monitoring flowering events. This information is valuable for studying climate change, assessing ecosystem health, and understanding the influence of environmental factors on plant life cycles.



Detection and classification of opened and closed flowers in grape inflorescences using Mask R-CNN

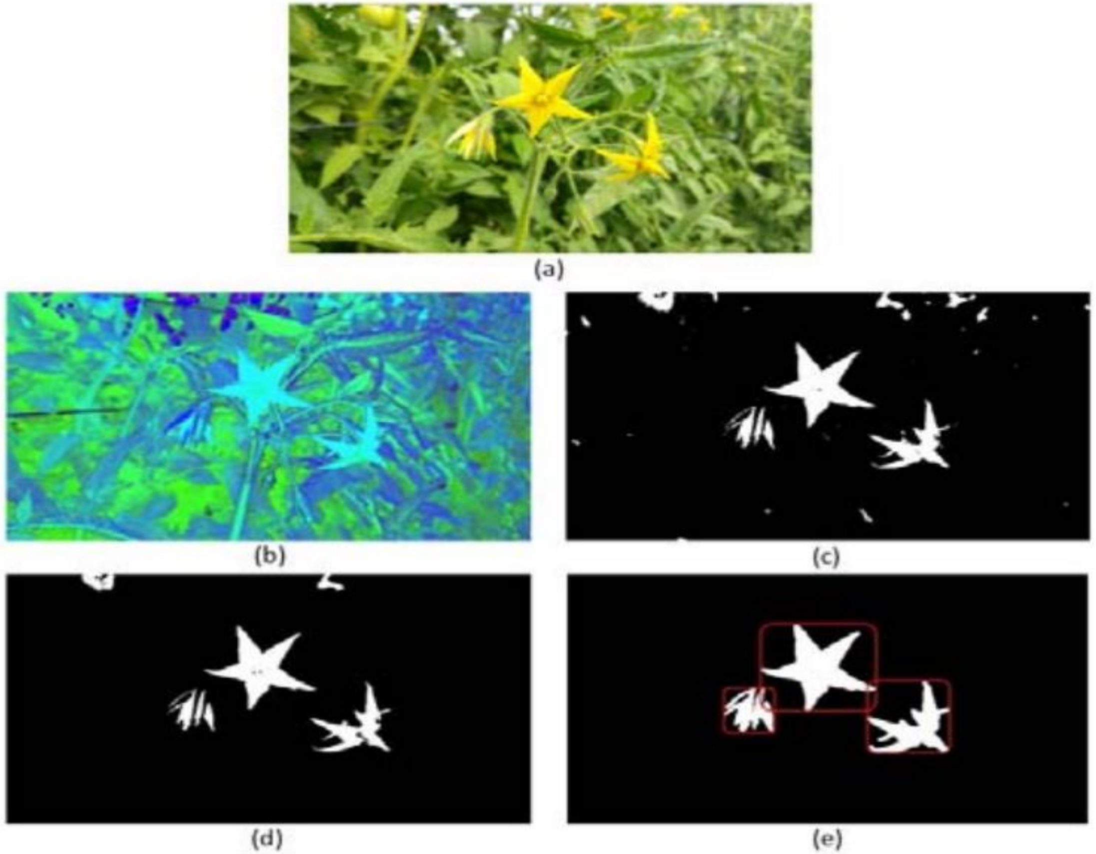


Fig. 6 An example of the main procedure of the proposed algorithm: (a) Original image, (b) HSV image, (c) After segmentation over H and S, (d) After noise removal, (e) Classification results (red rectangles are connected components classified as flowers)

Detecting Tomato Flowers in Greenhouses Using Computer Vision

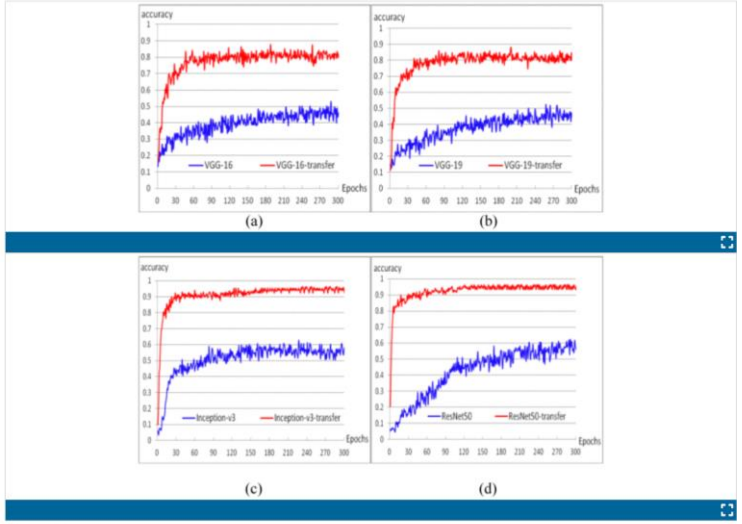


Figure 5
(a) (b) (c) (d) show the comparison of the accuracy of VGG-16, VGG-19, Inception-v3, ResNet50 initialization model and transfer model in the validation set of Oxford-17 flower dataset

Method	Accuracy of training set	Loss of training set	Loss of validation set
VGG-16	73%-74%	0.67	1.91
VGG-16-transfer	**98%-99%**	**0.07**	**1.90**
VGG-19	72%-73%	0.69	1.69
VGG-19-transfer	**98%-99%**	**0.04**	**1.66**
Inception-v3	96%-97%	0.08	2.03
Inception-v3-transfer	**99%-100%**	**0.01**	**0.29**
ResNet50	84%-85%	0.27	1.85
ResNet50-transfer	**99%-100%**	**0.002**	**0.24**

Results and Breakthroughs:

The Inception_v3 and ResNet50 transfer models exhibit faster convergence rates and smaller network losses compared to the VGG-16 and VGG-19 transfer models in all four types of transfer learning models.

Analysis of Figure 4 and Figure 5 supports the conclusion that transfer learning models demonstrate better robustness and generalization abilities than the initialization network model.

The random initialization network model is more prone to local optima issues and exhibits relatively poor robustness and generalization, likely due to its deep structure and a high number of training parameters.

Transfer models, with frozen specific network layer weight parameters and fully trained semantic level parameters, yield more distinguishable target features.

Conclusion

- Deep learning, especially through CNNs, has revolutionized identification methods, replacing manual feature engineering with enhanced accuracy and efficiency. The accessibility of diverse, annotated datasets, notably Oxford Flowers 102, has driven advancements across various flower species.Examining influential factors, such as dataset quality, image processing, feature extraction, and ML classifiers, reveals the evolving landscape.
- CNNs stand out for their hierarchical feature learning, transfer learning capabilities, and resistance to overfitting, enhancing the discernment of intricate flower characteristics.The literature review showcases breakthroughs with recognition rates exceeding 90%, illustrating deep learning's potential.
- Precision, recall, F1 score, and confusion matrices consistently prove superior accuracy over traditional methods. Innovative approaches like feature fusion, segmentation, and fine-grained classification further improve model capabilities.In conclusion, this comprehensive review provides insights into methodologies, datasets, and applications shaping the rapidly advancing field of flower classification. It underscores the transformative role of deep learning, specifically CNNs, and highlights the profound impact of technology on botany and ecological research.

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