MFCIS: AN AUTOMATIC LEAF-BASED IDENTIFICATION PIPELINE FOR PLANT CULTIVARS USING DEEP LEARNING AND PERSISTENT HOMOLOGY

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Introduction

Recognizing the plant cultivars reliably and efficiently can benefit plant breeding in property rights protection and innovation of germplasm resources. Although leaf image-based methods have been widely adopted in plant species identification, they seldom have been applied in cultivar identification due to a higher similarity of leaves among cultivars. Here, we proposed an automatic leaf image-based cultivars identification pipeline called MFCIS (Multi-feature Combined Cultivar Identification System), combining multiple leaf morphological features collected by persistent homology (PH) and convolutional neural network (CNN).

Materials and Methods

- **Plant Materials:** 5000 images per dataset

Dataset	Cultivar Number	Image Number Per Cultivar
Sweet Cherry	88	50~90
Soybean	100	50

- **Topological Feature Extraction by PH:** Persistent homology, a multi-scale and robust method, was deployed for extracting topological signatures of leaf shape, texture, and venation.

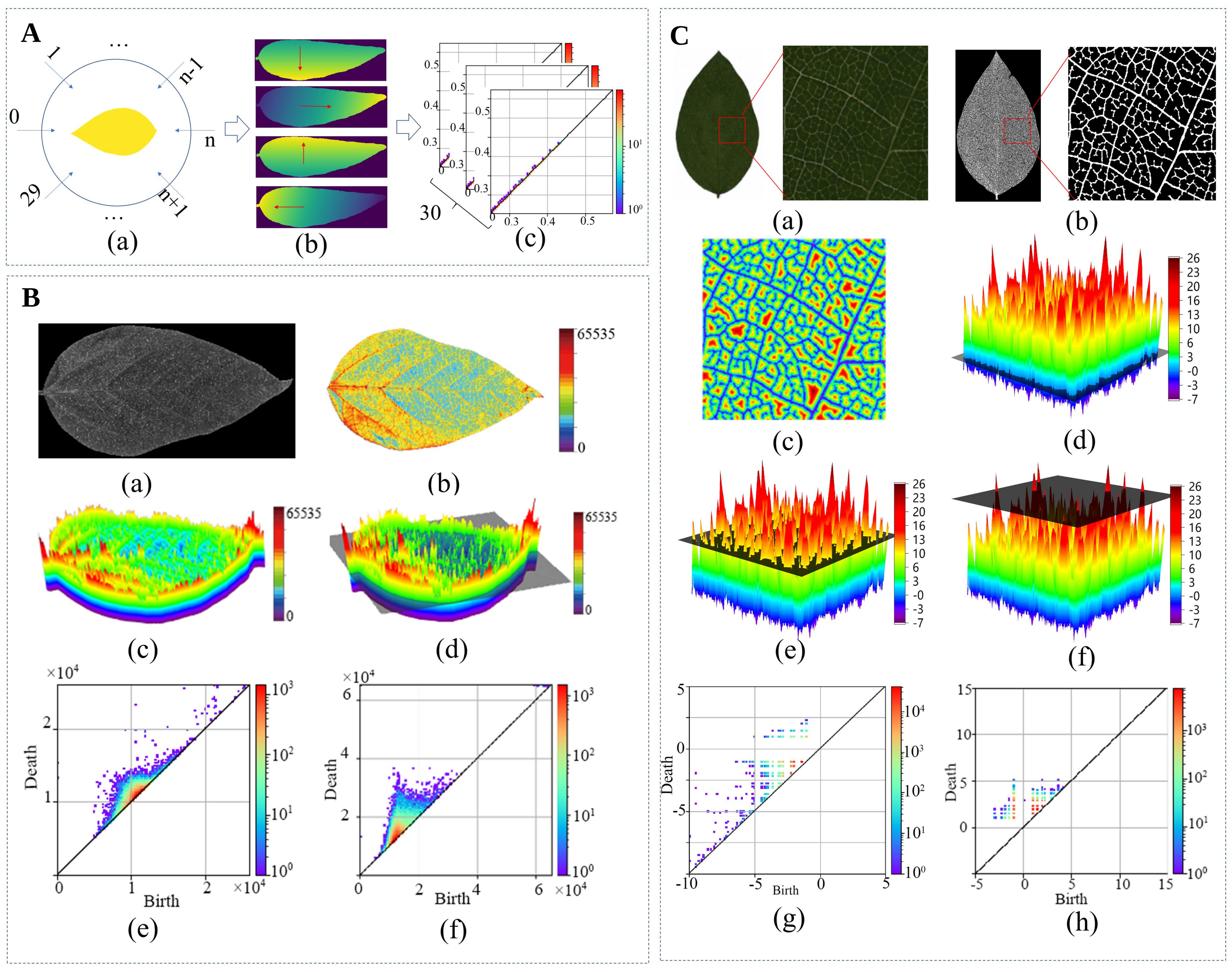

Figure 1. The procedure of leaf morphological features extraction using persistent homology.

- **High-level Image Feature Extraction by CNN:** The deep CNN model, Xception, was implemented as the backbone network to extract high-level features from leaf images

Results

1. The Online Cultivar Recognition System

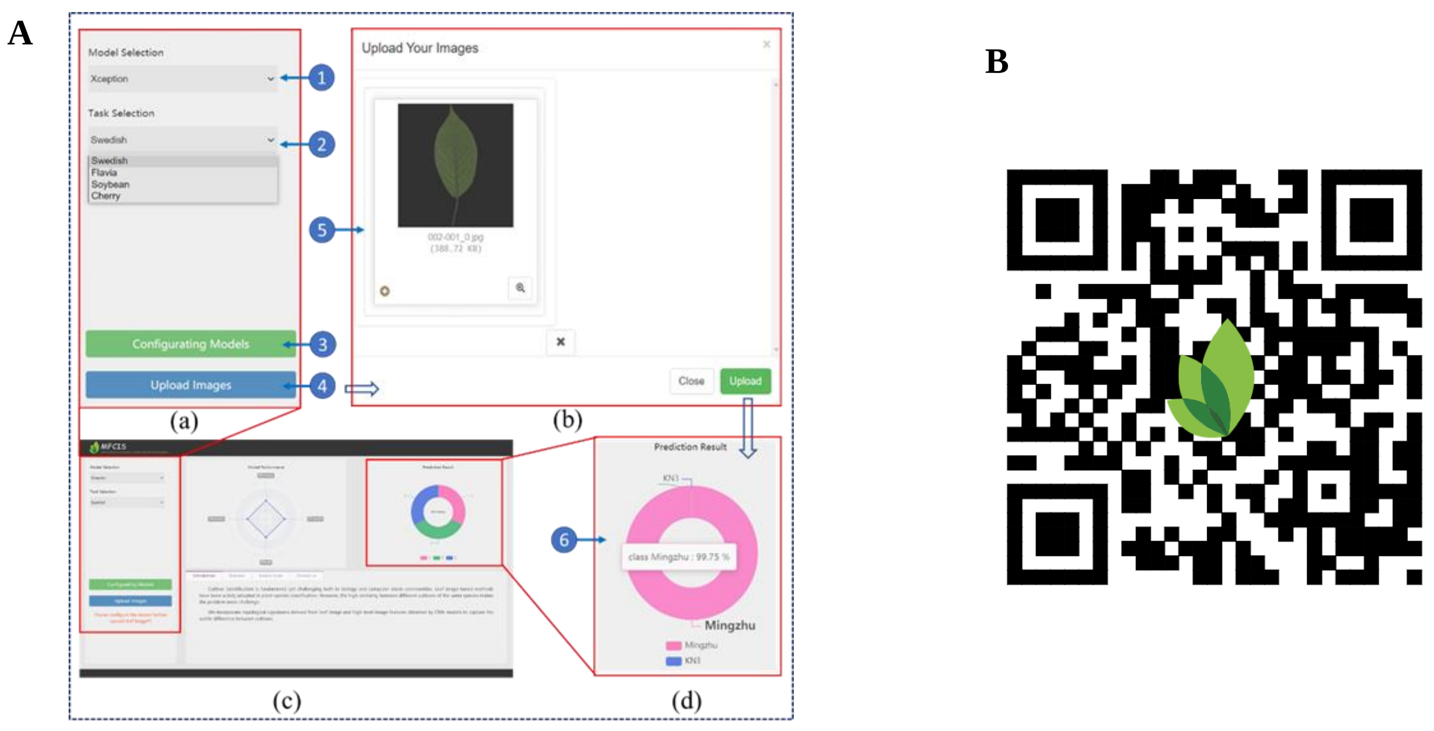

Figure 2. MFCIS system. (A) The main interface of the online cultivar recognition system. (B) QR code for MFCIS webpage .

2. Topological Features Extracted Using Persistent Homology

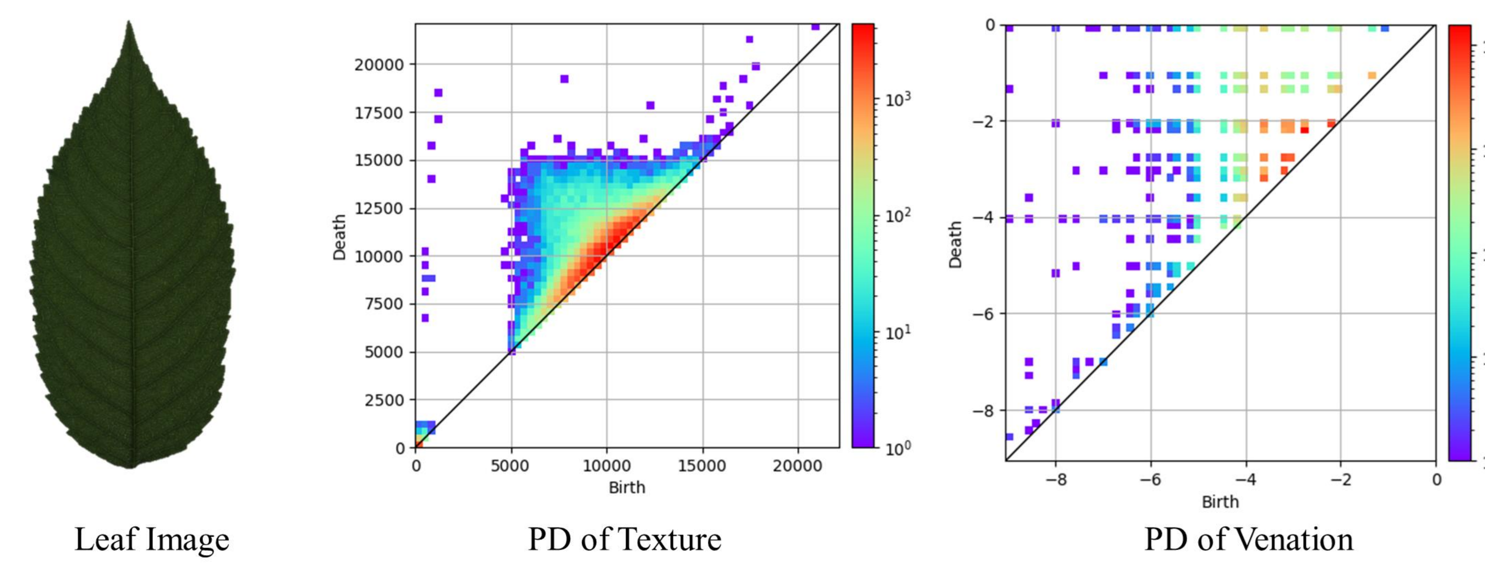

Figure 3. Examples of leaf texture and venation topological features.

3. Performance on Different Cultivar Datasets

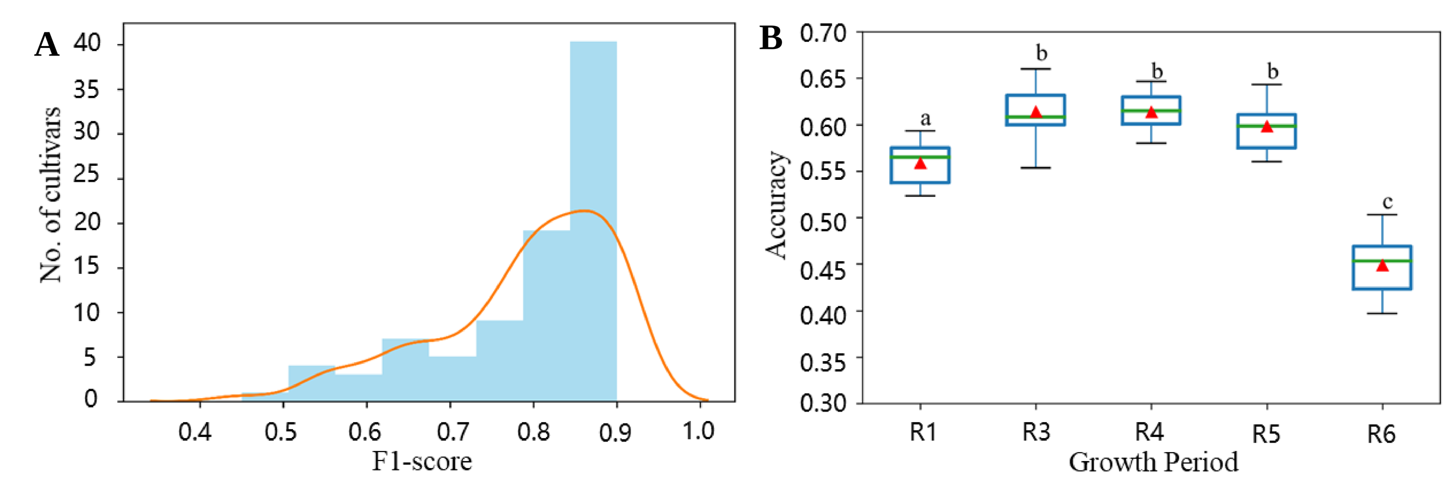

Figure 4. Results on Sweet Cherry and Soybean Cultivar Datasets. (A) The distribution of F1-score on the sweet cherry dataset. (B) Boxplot of the accuracy of cultivar identification using leaves of each period independently on the soybean dataset.

4. Performance of Score-level Fusion

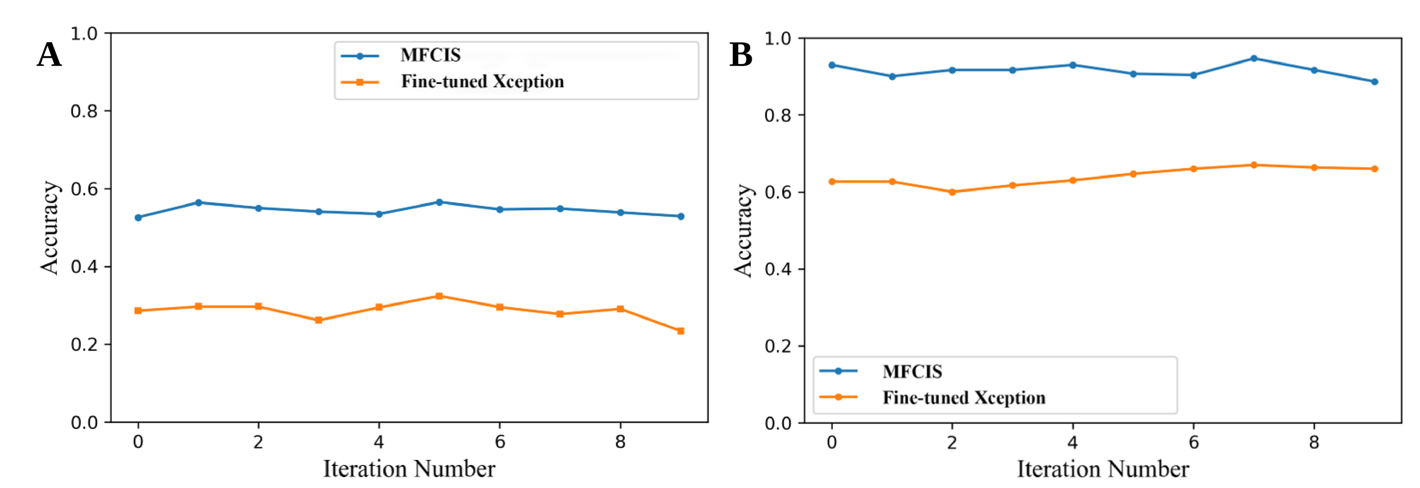

Figure 5. Comparison of mixing all growth periods (A) and fusing the results of different growth periods (B) on soybean dataset.

5. Performance Comparison With Other Methods

Table 1. Accuracies of different methods using leaves of each period independently on the soybean dataset.

Method	Accuracy (%)				
	R1	R3	R4	R5	R6
HSC	27.02	31.07	31.20	30.60	27.71
PH	16.70	17.15	18.20	17.25	12.70
Fine-tuned Xception	30.60	35.97	33.37	29.73	20.40
MFCIS (Our model)	**55.90***	**61.40***	**61.37***	**59.80***	**44.87***

Table 2. Comparison of classification accuracies of the different models on the sweet cherry dataset.

Method	Accuracy (%)
HSC	16.47
PH	42.08
Fine-tuned Xception	66.52
MFCIS (Our model)	**83.52**

Conclusion

This study proposed an effective strategy of leaf image acquisition, generated an image analysis pipeline for cultivar identification with high accuracy, and constructed a web-based and user-friendly cultivar identification platform.