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Conference Day 3 – October 21, 2017 (Saturday)		
08:00 – 09:00	**Registration** **Location**: Century Riverside Hotel	
08:30 – 09:45	**Session Sat-1A** **Computer Vision and Pattern Recognition - 1** **Chairs: Thanh-Ha Le and Tuong-Tri Nguyen** **Location:** Imperial Room	**Session Sat-1B** **Spatial Data Science and Technology - 1** **Chairs: Thi-Nhat-Thanh Nguyen and Viet-Hai Ha** **Location:** VIP 3 Room
08:30 – 08:55	***Facial Expression Recognition Using Deep Convolutional Neural Networks*** Sang Dinh, Dat Nguyen, and Thuan Do	***Paddy Rice Mapping in Red River Delta Region Using Landsat 8 Images: Preliminary Results*** Man Chuc, Anh Nguyen, Thuy Nguyen, Hung Bui, and Thanh Nguyen
08:55 – 09:20	***Plant Identification Using Score-based Fusion of Multi-Organ Images*** Binh Do, Hoang Nguyen, Nhan Nguyen, Hai Vu, Hai Tran, and Lan Le	***A Novel Approach Based on Deep Learning Techniques and UAVs to Yield Assessment of Paddy Fields*** Tri Nguyen, Hieu Duong, Hoai Tran, Hoa Tran, Vu Nguyen, Toan Nguyen, and Vaclav Snasel
09:20 – 09:45	***A New Approach for Traffic-Sign Recognition Using Sparse Representation over Dictionary of Local Descriptors*** Ha Do, Thang Nguyen, Dat Nguyen, and Tuan Le	***TMACT: A Thematic Map Automatically Creating Tool for Maintaining WebGIS Systems*** Thang Luu, Thanh Nguyen, Thuy Nguyen, and Hung Bui
09:45 – 10:00	***Coffee Break***	
10:00 – 11:15	**Session Sat-2A** **Computer Vision and Pattern Recognition - 2** **Chairs: Le-Minh Nguyen and Dang-Binh Nguyen** **Location:** Imperial Room	**Session Sat-2B** **Spatial Data Science and Technology - 2** **Chairs: Quang-Hung Bui and Thanh-Hieu Le** **Location:** VIP 3 Room
10:00 – 10:25	***Multi-Column CNNs for Skeleton Based Human Gesture Recognition*** Hai Nguyen, Nam Ly, Huong Truong, and Dung Nguyen	***Looking beyond Databases: Cyberinfrastructure That Supports Data-Sharing and Collaborations*** Tho Nguyen
10:25 – 10:50	***Single View Image Based - 3D Human Pose Reconstruction*** Kien Hoang, Hung Nguyen, Chau Ma, Duyen Ngo, and Thanh	***Anomaly Color Detection on UAV Images for Search and Rescue Works***

	Nguyen	Hoai Dao and Phuong Nguyen
10:50 – 11:15	***Facial Smile Detection Using Convolutional Neural Networks*** Sang Dinh, Cuong Le, and Thuan Do	***Development of Virtual Campus Using GIS Data and 3D GIS Technology: A Case Study for Vietnam National University, Hanoi*** Anh Phan, Chuc Man, Hung Bui, and Thanh Nguyen
13:30 – 17:30	**Hue City Tours**	

Plant Identification using score-based fusion of multi-organ images

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***Abstract*—This paper describes a fusion technique for species identification from images of different plant organs. Given a series of image organs such as branch, entire, flower or leaf, we firstly extract confidence scores for each single organ using a state-of-the-art deep convolutional neural network (CNN). After that, we deploy various schemes of the fusion approaches including not only conventional transformation-based approaches (sum rule, max rule, product rule) but also a classification-based approach (support vector machine). Then we proposed a hybrid fusion model. To measure the performances of the combination schemes, a large number of images of 50 species which are collected from two main resources: PlantCLEF 2015 dataset and the Internet resources. The experiment exhibits the dominant results of the fusion techniques compared with those of individual organs. At rank-1, the highest accuracy of a single organ is 73.0% for flower images, whereas by applying our proposed fusion technique for leaf and flower, the accuracy reaches to 89.8%.**

***Index Terms*—Convolutional Neural Network, Deep Learning, Fusion, Plant Identification.**

I. Introduction

Plant identification plays an important role in our daily life. Nowadays, automatic vision-based machines for the plant identification usually utilizes image(s) from individual plant organ such as leaf [1], [2], [3], flower [4], branch [5] etc. They have gained a considerable attention of researchers in the fields of multimedia retrieval, computer vision and pattern recognition. In recent competitions for the plant identification (e.g., PlantCLEF 2014, 2015, 2016 and 2017), deep learning technique has emerged as an efficient tool. However, with a large number of species, the accuracy of the identification task using a single organ is still limited. Beyond the performance issues of the classifiers, using images from individual plant organ has also some practical and botanical limitations. For instance, the appearance of the leaf can be easily changed by temperature, weather condition. Some leaves of specific species are often too young or too much depends on periods of the year. The appearance of flowers is more stable and less variant with such changes. Some organs (e.g., flower, or fruit or even leaves) are not visible all over the year. Following the point of view of botanists and biological experts, images from alone plant organ could not be enough information for the identification task. They also comment that there are many practical situations where separating species can be very difficult by just observing leaves, while it is indisputably easier with flowers. In this paper, we propose to use combinations of multi-organ images using some fusion techniques, which combine the confidence scores from some single organs. The main objectives of the study are to answer following questions: which fusion approach is the most effective; and a combination of which pair of organs returns the best performance. The fusion techniques are: (1) transformation-based approaches [6] such as sum rule, max rule, and product rule; (2) classification-based approaches [6]; (3) our proposed robust hybrid fusion (RHF). Each pair of organs is combined and examined with these fusion approaches. We experiment in four types of organs: leaf, flower, branch and entire because they are more common than other ones (e.g., fruit, stem, root). We firstly deploy a deep CNN that could achieve the higher performance than conventional hand-designed feature approaches. However, it is noticed that the performances of a CNN strongly depend on image varieties within each species in the training dataset. The performances of the plant identification task could be increased when the number of images for each species is large enough. Specially, a large number of images of each plant organ with same species is required in context of the multi-organ combination. Therefore, we take into account collecting the images of different organs of same species for the context of the multi-organ combination. Our proposal fusion methods show a significant improvement compared with the identification accuracy of images from an individual plant organ. The rank-1 accuracy of the identification increases more than 10% by fusing flower and leaf with product rule and the proposed robust hybrid fusion.

This paper is organized as follows: Section II surveys relevant works of the plant identification and the fusion approaches. The single organ identification using a convolutional neural network is described in Section III. In Section IV, we present the combinations of multi-organ images with various fusion schemes. Section V shows the experimental results. The conclusion and discussions are given in Section VI.

II. Related work

A. Plant identification

Since the last decade, the plant identification tasks mainly utilize images from leaves on a simple background [7], [8],

[9], [10], [11] because leaves usually exist in whole year and are easily collected. However, leaves often do not have enough information to identify a plant species. The plant identification task has recently been expanded with images [12], [13] from different organs such as leaf, flower, fruit, and stem, entire on complex background so that the identification rates are better. The performances of the recent approaches are listed in a technical report of the LifeCLEF 2015 [5]. Readers can also refer a recent comprehensive survey on plant species identification using computer vision techniques in [14].

There are two main approaches for the plant identification task. The first one uses hand-designed feature [15], [16], [7] where the automatic vision-based machines applied a variety of generic feature extraction and classification techniques. The common features [14] are morphological, shape-based, color, textures, while the Support Vector Machines (SVM) and Random Forest (RF) are common classifiers. These approaches are steady but achieve low performances when facing with a large number of species such as 500 species in PlantCLEF 2014, 1000 species in PlantCLEF 2015/2016 datasets [5]. The second one employs the deep learning techniques. Convolutional neural networks (AlexNet, VGGNet, GoogLeNet and ResNet) obtained state-of-the-art results in many computer vision tasks [17], [18]. The teams utilizing deep learning techniques are top winners in PlantCLEF 2014 competition [19]. The winner used AlexNet from scratch to classify 500 plant species. Continuing this success, many research groups have used the deep learning approaches for the plant identification [5], [20]. GoogLeNet and VGGNet are used by most teams in the PlantCLEF 2015/2016 competition, including the winning team. In [21], a CNN is used to learn unsupervised feature representations for 44 different plant species collected at the Royal Botanic Gardens, Kew, England. Nhan et al. [22] carried out and analysed a comparative evaluation between hand-designed features and deep learning approaches. They show that CNN-based approaches are significantly better than the hand-designed schemes.

The fact that the state-of-the-art results of the plant identification using a single organ are still far from practical requirements. For example, the current best rank-1 accuracy of the plant identification is approximately 75% by using flower images. In our empirical evaluation, this performance is significantly reduced when the number of species is increased. The classifiers utilizing the image(s) from individual organs face a challenge that is the small variation among species, and a large variation within a species. Therefore, some recent studies propose the combinations of multiple organs of plants [12], [13]. The late fusion techniques are the common ways to combine identification results from the single organs. The authors in [22] showed that a combination of leave and flower images produces positive results. In this paper, we examine various score-based level fusion to answer the questions that which ones achieve the best performances and which pair of organs could achieve the best identification results.

B. Summary of fusion information techniques

According to the information fusion theory, fusion schemes could be divided into four categories [23]: sensor level, feature level, score level, and decision level. Sensor level fuses the raw data from varied source at image level or pixel level. For example, a 2-D image of face and the structure of this face could be combined to construct a 3-D image. Feature level fusion [23] combines two or more feature vectors into an individual one. They should be normalized to a common scale before the fusion. For example, Arun et al. [24] deployed a human recognition system by applying the fusion strategies for hand and face at feature level. He et al. [13] used a multi-column deep convolutional neural network for multi-organ plant identification. The inputs of each column are the different organs of the plant. He used AlexNet for features extraction in each column before fusing all of it by some fully connected layers. The score-based level approaches utilize the similarity or confidence scores between an input/probe features and the template ones in the gallery. These approaches combine the scores from different sources to a unique form which is able to deploy as common classification. In decision level fusion, the results from different sources are combined using several techniques, such as AND and OR Rules, Bayesian decision fusion [24], to provide the final one. Although the matching/confidence scores contain less information than the raw image or the feature vectors, they hold the most important information on the identification/classification task. Utilizing the matching/confidence scores is also easier to deploy various fusion strategies. For this reason, in this study, we deploy score-based fusion schemes which aim to combine matching scores from images of individual plant organs for resolving the plant identification task.

C. The score-based level fusion strategies

The score level fusion can be categorized into three groups: transformation-based approaches, classification-based approaches, and density-based approaches [6]. In transformation-based approaches, the matching or confidence scores are normalized first. Then they are fused by using various rules, such as min rule, product rule or sum rule, to calculate a final score. The final decision then is marked based on that score. Nhan et al. [22] used the sum rule to combine identification results from leaf and flower images and got the better result than single organ. In classification-based approaches, multiple scores are treated as feature vectors and a classifier, such as Support Vector Machine and Random Forest, is constructed to discriminate each category. The signed distance from the decision boundary is usually regarded as the fused score. The last group, density-based approaches guarantee the optimal fusion as long as the probability density function of the score given for each class is correctly computed. However, such kind of approaches are suitable only for verification issue, but not for identification task. In this paper, we deploy two first types of the score-based level fusions: transformation-based, and classification-based approaches. We apply sum rule, max rule and product rule for the transformation-based approaches. We build a SVM classifier using the confidence scores of different plant organs for the classification-based approaches.

III. Single organ identification using convolutional neural networks

AlexNet, which is developed by Alex Krizhevsky, Ilya Sutskever and Geoff Hinton [18], is the first CNN that has become the most popular nowadays. It succeeds in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) dataset [25] with roughly 1.2 million labeled images of $1,000$ different categories. The AlexNet's architecture [18] is shown in Fig. 1. It has approximately 650,000 neurons and 60 million parameters. There are five convolutional layers (C1 to C5), two normalization layers, three max-pooling layers, three fully-connected layers (FC6, FC7, and FC8), and a linear layer with a softmax classification in the output. In this study, Alexnet is deployed on a common PC with two Intel Core i5, 01 Nvidia Geforce GPU 4 GB, 16 GB RAM. We fine-tuned AlexNet with the pretrained parameters of AlexNet in ImageNet dataset. The output of the softmax function is 50 classes instead of 1000 classes as the default. The main reason is that AlexNet runs quite fast on common PC or workstation and achieves comparative results compared with some recent CNNs such as GoogleNet, VGGNet. On the other hand, we focus more on fusion approaches than improving the result for each single organ.

In the test phase, the output matching/confidence scores obtained for an image is an n-dimensional vector $S = \{s_i\}$, $0 \leq s_i \leq 1$, where n is the number of species. This vector refers the confidence scores to all available species. In other words, it is a prediction for a certain species. As notated, $\{s_i\}$ is the confidence score to i^{th} plant species.

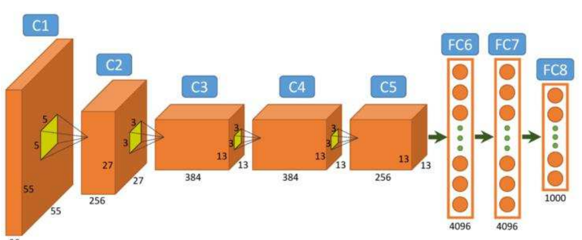

Fig. 1. AlexNet architecture [18]

IV. The proposed fusion strategies

A. Transformation-based approaches

We combine the identification results from N images of two organs as the following rules. Given q is the query-images of a pair of organs, $score(I_i, species)$ is the matching or confidence score when using image I_i as a query from a single organ.

Max rule is one of the most common transformation-based approaches. Maximal score is selected as the final score:

$$score(q, species) = \max_{i=1}^{N} score(I_i, species) \tag{1}$$

Sum rule is also the representative of the transformation-based approaches. Summation of the multiple scores provides a single fused score. It is defined by:

$$score(q, species) = \sum_{i=1}^{N} score(I_i, species) \tag{2}$$

Product rule is based on the assumption of statistical independence of the representations. This assumption is reasonable because observations (e.g., leaf, flower, entire) of a certain species are mutually independent. This allows us using images from multi-organ in order to make a product rule for the plant identification task. The product rule is defined by:

$$score(q, species) = \prod_{i=1}^{N} score(I_i, species) \tag{3}$$

B. Classification-based approaches

The score-based level fusion can be formed as a classification-based approach. Once the multiple confidence scores are concatenated into a single feature vector, we can build a binary or multiple classifier. In this study, we adopt works in [6] which deploys a classification-based approach for fusing multiple human gait features. The plant identification task is formed as a one-versus-all classification. We define a positive/negative sample as a pair of scores at the true/false position of species. Positive and negative samples are chosen as shown in the Fig. 3. A SVM classifier is trained by using positive and negative training samples in the score space.

The distribution of positive and negative samples, which are obtained from confidence scores of branch and leaf images, is shown in Fig. 2. In the test phase, after pushing a pair of organs into CNNs model, we have a pair of score vectors correspondingly. We split it into n pairs where n is the number of species. Then we push each pair into SVM classifier and we keep it if it is a positive sample. The species of the positive sample, which has maximum distance to the decision bound, is the label of pair of organs.

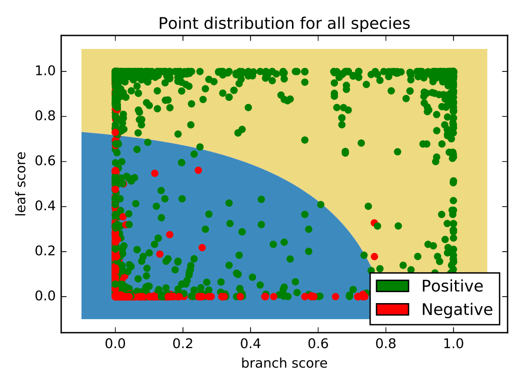

Fig. 2. Distributions of negative and positive samples formed based on the branch and leaf scores

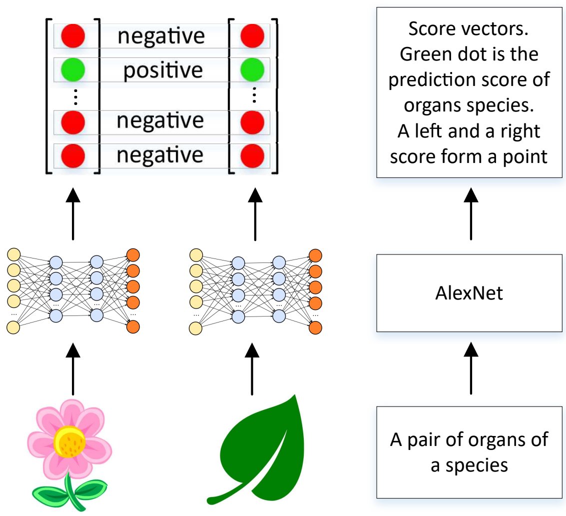

Fig. 3. Explaination for positive and negative samples

C. The proposed robust hybrid fusion

The above classification-based approach can lose distribution characteristics for each species because all positive and negative samples of all species are merged and represented in a metric space only. Therefore, we build each species a SVM model based on its positive and negative samples. For example, Fig. 4 shows a score's distribution of a specific species. When we input a pair of organ to our model, we will know the probability that it belongs to each species by these SVM classifiers. Then we combine this probability with the confidence score of each organ. As far as we know, q is the query of a pair of two image organs; and $score(I_i, species)$ is matching or confidence score when using image I_i. Let's denote the probability $prob_{pos}$ that q is a positive sample of the $species$ SVM model. Our robust hybrid fusion model therefore is formed as independence observations:

$$score(q, species) = prob_{pos}\left(\prod_{i=1}^{N} score(I_i, species)\right) \quad (4)$$

This model is an integration between a product rule and a classification-based approach. We expect that the positive probability of point q affects the fusion result. If the positive probability of point q is high, the probability of point q belonging $species$ is high, too.

V. Experimental Results

A. Collecting the database

The proposed fusion strategies are evaluated with four types of organs including: leaf, flower, entire and branch. For deploying a CNN successfully, it always requires a large training data. Moreover, for deploying multi-organ plant identification, we must be ensured with different organs of same species. The fact that even with a large PlantCLEF 2015 dataset, there are only 12.5% observations that have at least 2 organs [13].

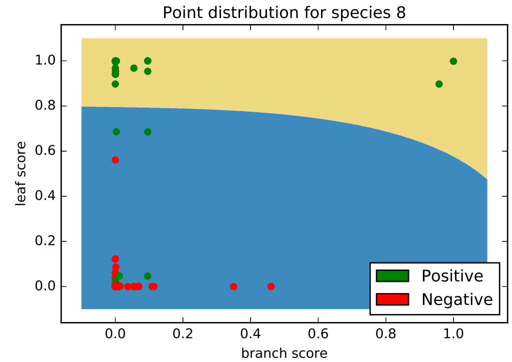

Fig. 4. Distributions of negative and positive samples formed based on the branch and leaf scores for species id 8

TABLE I
The collected dataset of 50 species with four organs (Leaf, Flower, Entire and Branch images)

	Flower	Leaf	Entire	Branch	Total
CNN Training	1649	1930	825	1388	5792
SVM Input	986	1164	493	833	3476
Testing	674	776	341	553	2344
Total	3309	3870	1659	2774	11612
	Species number = 50				

In this study, we deploy the following scheme in order to enrich the experimental dataset of the plant species. Firstly, we extract the most common species (the species with the largest number of images) from PlantCLEF 2015 dataset [5] which is collected from West Europe with more than one hundred thousand pictures of 1000 plant species. PlantCLEF 2015 dataset is one of the largest plant dataset in the world. As result, we collect 50 species which consist of largest number of observations. We used Bulk Image Downloader, which is a powerful tool for collecting images from Internet resources, to collect more data using species' name. The searching results are manually screened later. The details of our final evaluation dataset are shown in Table I. The average of images for each organ of each species after enrichment is larger than 50. This is larger than the original of PlantCLEF 2015 dataset.

The collected dataset is separated into three parts with the ratio 5:3:2 respectively. The first part is the training data of CNN for single organ identification, as explained in Section III. We used the third part of the dataset to evaluate the performances of CNN and late fusion methods. For the fusing based on classification approaches, to deploy a SVM classifier, the results from the second part of the dataset returning from CNN was used as training dataset of the SVM model. In order to balance the number of positive and negative sample, we randomly collect the negative points instead of taking all of those. The proposed hybrid fusion scheme utilizes the testing schemes of the product rule and the classification-based approaches.

TABLE II

THE ACCURACY RATE OF THE PLANT IDENTIFICATION USING IMAGES FROM SINGLE PLANT ORGAN

Organ	Rank-1 (%)	Rank-5 (%)
Leaf (Le)	66.2	89.8
Flower (Fl)	73.0	90.8
Branch (Br)	43.2	70.4
Entire (En)	32.4	64.0

B. Evaluation measurement

We use an accuracy rate of the identification to evaluate the performances of the proposed fusion approaches. It is defined by:

$$Accuracy = \frac{T}{N} \tag{5}$$

where T is the number of true predictions, N is the number of queries. A query is correctly identified if the relevant plant is in the k first species returned from the retrieved list. We compute accuracy at rank-1 and rank-5 in our experiments.

C. Experimental results

The experimental results show that all the fusion techniques highly improve the accuracy rate compared with utilizing images from an individual organ. As clearly shown in Table II and Table III, the best performance for single organ is 73.0% for flower images, whereas by applying the proposed RHF, the accuracy rate of a combination between leaf-flower images dramatically increase by 16.8% to 89.8%. Not only the leaf-flower scenario, but in all six pairs of multi-organs combination, the product rule and its variants RHF also retain the highest performances. The other fusion performances are also higher than those of single organ, but lower than these fusion schemes.

We continue evaluating the performance of the proposed fusion schemes using Cumulative Match Characteristic curve (CMC), as shown in Fig. 5. It measures the plant identification performances at various rank. The better performance, the higher CMC is achieved. The higher CMCs are obtained with the most of fusion schemes. The best CMC is obtained by combination of Flower-Leaf with the RHF fusion.

In order to further evaluate advantages of the proposed fusion schemes, we attempt to find out the rank-k so that the accuracy of the plant identification reaches 99%. In this evaluation scenario, the fusion performances are better than those of single organs. The detailed results are given Table IV. Besides, the RHF and product rule continue showing the significant performance compared with the results of other techniques. With leaf-flower combination, it can reach the accuracy 99% at rank-7 for Product Rule, or rank-9 for RHF. This is much lower than the best case of using images from a single organ, where rank-27 is required.

TABLE III

THE ACCURACY RATE OF TWO-ORGANS COMBINATIONS

Accuracy (%)		Max rule	Sum rule	PR	SVM	RHF	MC
En - Le	R1	66.2	67.2	75.6	74.0	**76.6**	46.7
	R5	88.6	88.8	93.2	81.8	**94.6**	70.8
En - Fl	R1	73.8	74.4	78.8	77.2	**81.2**	73.7
	R5	92.6	92.8	94.2	84.2	**94.4**	90.8
Le - Fl	R1	81.6	82.0	88.6	86.2	**89.8**	74.2
	R5	96.8	96.8	98.2	90.4	**98.4**	90.5
Br - Le	R1	70.2	71.0	76.8	73.8	**78.4**	39.8
	R5	89.6	90.0	93.4	79.6	**93.8**	67.5
Br - Fl	R1	74.2	75.4	80.8	79.0	**81.4**	64.1
	R5	90.8	91.4	95.2	83.0	**95.4**	84.0
Br - En	R1	51.6	52.2	58.0	58.0	**58.6**	34.2
	R5	76.8	77.6	83.6	81.4	**83.8**	58.8

[1]PR means Product rule. [2]The result of MC [13] is for reference only because of our different evaluation environments.

TABLE IV

RANK NUMBER (K) TO ACHIEVE THE ACCURACY RATE OF 99%

	En-Le	En-Fl	Le-Fl	Br-Le	Br-Fl	Br-En
Organ 1	42	42	**27**	46	46	46
Organ 2	**27**	29	29	**27**	29	42
Sum rule	17	24	10	21	25	25
Max rule	19	24	10	23	25	26
Product rule	16	20	**7**	22	18	25
SVM	50	50	50	50	50	50
RHF	14	19	**9**	19	18	25

VI. CONCLUSIONS

This paper examined various fusion schemes for the plant identification using multi-organ images. The experiments show that the fusion techniques increase dramatically the performances for the plant identification task. In addition, our robust hybrid fusion model presents the best results in all evaluation. It is an evidence for the statement that the results from CNN of single organs are independent. In future work, we attempt to find the way to automatically combine the results without knowing the type of organs. It is clear that, in most situations, an image could contain more than one organ. Therefore, our second task is to automatically detect the type of organ or a learning scheme so that weight of the organ can be identified. By combining two tasks, we support the end-user getting the high performance without knowing which type of organ actually is or even automatically investigating semantic organs in the queries.

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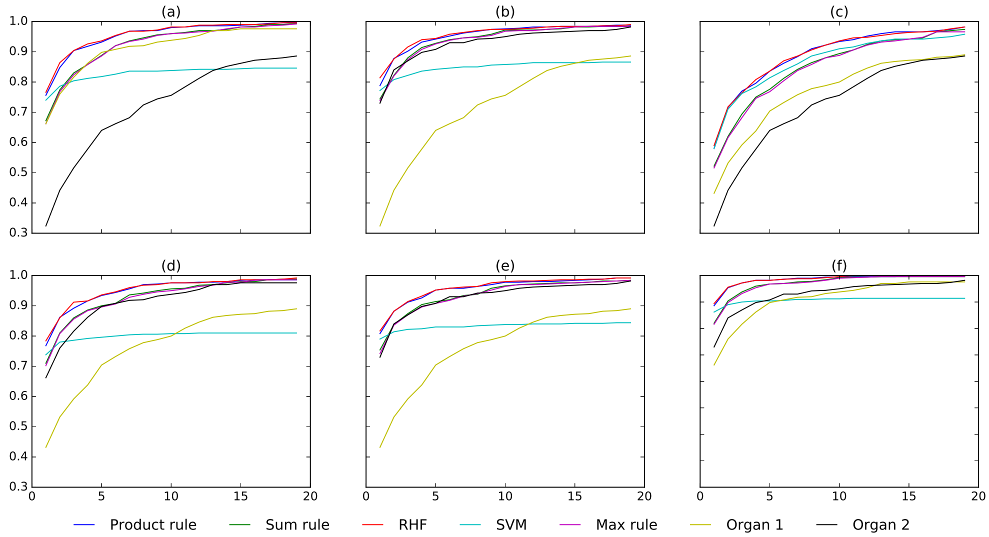

Fig. 5. Cumulative Match Characteristic curve of (a) Leaf-Entire; (b) Entire-Flower; (c) Branch-Entire; (d) Branch-Leaf; (e) Branch-Flower; (f) Leaf-Flower

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