

**PUNE INSTITUTE OF COMPUTER TECHNOLOGY,
DHANKAWADI PUNE-43.**

A Seminar Report

On

Identification of Image-Based Plant Species using Single and Multiple Organ Images

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CERTIFICATE



This is to certify that Mr. ***Shantanu Jain*** , Roll No. **3363** a student of T.E. (Computer Engineering Department) Batch 2017-2018, has satisfactorily completed a seminar report on “**Identification of Image-Based Plant Species using Single and Multiple Organ Images**” under the guidance of Prof. M. S.Chavan towards the partial fulfillment of the third year Computer Engineering Semester II of Pune University.

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Identification of Image-Based Plant Species using Single and Multiple Organ Images

Contents

1	INTRODUCTION	6
1.1	Motivation	6
1.2	Literature Survey:	7
1.2.1	Plant identification:	7
1.2.2	The Score-based Level Fusion Strategies	7
2	SINGLE ORGAN PLANT IDENTIFICATION	8
3	PROPOSED FUSION TECHNIQUES:	9
3.1	Transformation-Based Approaches	9
3.1.1	Max Rule:	9
3.1.2	Sum Rule:	9
3.1.3	Product Rule :	9
3.2	Classification-Based Approaches	10
3.1.3	Support Vector Machine Based :	10
4	EXPERIMENTAL RESULTS:	11
4.1	Collecting the dataset:	11
4.2	Experimental Results :	12
5	CONCLUSION AND FUTURE ENHANCEMENT	14
5.1	Conclusion	14
5.2	Future Enhancements	14

List of Figures

- | | | |
|---|--|----|
| 1 | Distributions of negative and positive samples formed based on the branch and leaf scores | 10 |
| 2 | PR means Product Rule. The result of RHF and MC are put up as references only because of the variation in evaluation environments. | 14 |

List of Tables

Abstract:

The involvement of automated modern computing for increasing the productivity and efficiency in the agricultural field is imperative with the growing concerns of population and lack of farmers. One of the most important problems is the automatic identification of plant species on the basis of their types. We propose a Convolutional Neural Networks architecture for classifying the plants based on the images collected from a subset of PlantView dataset. In this seminar, we have looked at various fusion techniques for the identification of plant species using images from different plant organs. Firstly, we calculate the single organ probability scores for each of the specie, given a series of image organs like branch, leaf, flower or entire. After that, we enhance the model by fusing the features of multiple organs, using not only, conventional transformation-based approaches (sum rule, product rule, max rule), but also classification based approach (support vector machine). Finally, for checking the accuracy of the model proposed, we tested it against a set of 50 test plant species available as part of the PLANTCLEF-2015 dataset.

Keywords: Agriculture, Computer Vision for Graphics, Convolutional Neural Networks, Self-supervised learning, Machine learning, Fusion.

1 INTRODUCTION

Plants are the support systems for all of life on the earth, bestowing upon us continuous supply of essential resources like food and oxygen. An in-depth understanding of plants is crucial to help identify new or rare plant species for the enhancement of the drug industry, maintaining an ecological balance as well as for enrichment of agricultural growth and sustenance. To achieve this, accurate knowledge about the species is required. However, even for professional botanists, identification of plant species just by looking is a very difficult task.

Now-a-days, automatic vision oriented machines are deployed for identification of plant species, which mainly identify the plant by utilizing images from a single organ like flower, leaf, branch or entire. Convolutional Neural Networks have emerged as the leading performer in image retrieval tasks. However, as the number of the plant species increases, the accuracy of the model using a single organ is hampered. Moreover, beyond the performance limitations, using individual plant organs to identify plant specie has some practical limitations. For instance, a leaf of a plant may easily be altered due to temperature and weather fluctuations, and also their appearances depends on various periods in an year. On the other hand, flowers are more stable and are less affected by variations in the environment. Thus, in this seminar, we intend to use combination of images from multiple organs using variety of fusion techniques for achieving improved accuracy.

The fusion techniques are categorised as : 1. Transformation-based approaches, 2. Classification-Based Approaches. For experimentation, we have used four organs namely, leaf, branch, flower and entire. Firstly, we fine tune an AlexNet CNN model to calculate the confidence scores for single organ plant specie identification, then combine them using various fusion techniques for achieving better performance.

1.1 Motivation

Since the last decade, the plant identification tasks mainly utilize images from leaves on a simple background 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 from different organs such as leaf, flower, fruit, and stem, entire on complex background so that the identification rates are better.

Researchers in computer vision have used variations of leaf characteristics as a comparative tool to classify plant. Although the structural features of a leaf play an important role in the plant identification task, for certain plants, such as deciduous plants or semi-evergreen plants, leaves are not available over different periods of the years. Moreover, some species are hard to be differentiated using only their leaf organ as leaves in nature might have very similar shape and colour.

Inspired by the deep learning breakthrough in image classification, more researchers have started to use deep learning models such as the CNN, to learn a robust plant image representation. In this work, we employ a CNN model to build a plant classification system. We repurpose the current state-of-the-art AlexNet Model to incorporate species and organ features and solve the multi-organ plant classification problem.

1.2 Literature Survey:

1.2.1 Plant identification:

Since, the last decade, the image based plant specie identification involved mainly leaves on a simple background, as leaves are the most basic organs of the plant which can easily be collected. However, leaves, though easy to collect, do not provide sufficient information regarding the plant. Recently, the plant species identification tasks have aggravated their dataset by involving image identification using not just leaves, but also through flower, branch, fruit, stem, etc. The performances of the recent approaches are listed in a report by LifeCLEF 2015. Also, the viewers can refer to the comprehensive survey on plant species identification using computer vision techniques.

There have been two approaches that have been emphasized for plant identification. The first one uses feature which are hand designed, and uses automatic vision-based machine to extract generic features. The common features are shape-based, texture, color, using Support Vector Machine as a common classifier. These approaches, though steady, provide degraded accuracy when provided with a large dataset such as of PlantCLEF 2015, having 1000 species.

The second approach, and a more efficient one involves, utilising deep learning architectures. Convolutional Neural Networks turned out to be the most favourable techniques for obtaining state-of-the-art results in various computer vision tasks. In PlantCLEF 2014 competition, the winners developed an AlexNet model from scratch for classifying 500 species. Continuing this success, many research groups have started using deep learning architectures for training their model.

1.2.2 The Score-based Level Fusion Strategies

The score level fusion strategy can be classified into three groups: transformation-based, classification-based, and density-based. In transformation-based, the confidence scores are first normalized and then are fused by using various rules, such as min rule, max rule, product rule for calculating final 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 of organs are treated as feature vectors, and are classified using a SVM or Random Forest classifier. The signed distance from the decision boundary is usually regarded as the final score.

The final group, that is, the density based-approaches, guarantee optimal fusion as long as the

probability density function score for each class is computed correctly. However, density-based approaches are only suitable for verification issues, not for identification, thus are not referred in this seminar.

2 SINGLE ORGAN PLANT IDENTIFICATION

For the identification of plant species using single organ images, we have fine-tuned an AlexNet model. AlexNet, developed by Alex Krizhevsky, Geoff Hinton and Ilya Sutskever[18], is the most popular CNN model having approximately 65000 neurons and a total of 60 million parameters. The AlexNet architecture[18] is shown in Fig 1.0. The AlexNet consists of five convolutional layers (C1 to C5), three max-pooling layers, two normalization layers and three fully connected layers(FC6 to FC8), along with a softmax classifier at the output. The AlexNet has been configured to classify 50 classes instead of the default 1000.

The output at the end of the softmax layer is a n-dimensional vector of probability/confidence scores, $S = \{s_i\}$, where $0 \leq s_i \leq 1$, n denotes the number of species, in our case is 50. Thus, these scores predict the species based on the features extracted from a single plant organ image. Thus, as notated, $\{s_i\}$ denotes the confidence score for the i th plant species.

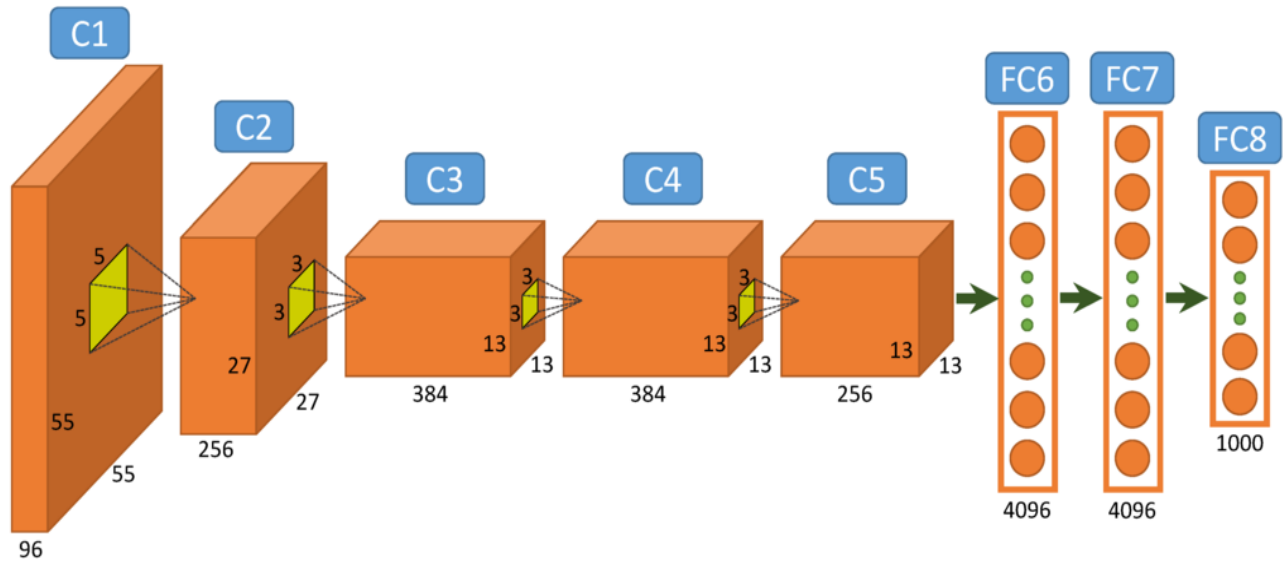


Fig 3. AlexNet Architecture

3 PROPOSED FUSION TECHNIQUES:

As mentioned earlier, using images of single organ for the identification of plant species has many limitations. Firstly, they vary with temperature, pressure and seasons. Moreover, it has been observed that there are many practical situations where identifying plant species based on their leaves, for instance is difficult, even for professional botanists. Thus, confidence scores from multiple organs are fused together to accurately identify the species in an efficient manner.

The probability scores obtained from the single organ plant identification is combined in the following manner, given 'q' is the query-images for a pair of organs, $\text{score}(I_i, \text{species})$ is the matching or confidence scores for an image I_i from a single organ.

3.1 Transformation-Based Approaches

3.1.1 Max Rule:

It is one of the most common transformation-based approaches. In this method, the maximum score from the set of confidence scores of multiple organs is used, that is,

$$\text{score}(q, \text{species}) = \max_i^n \text{score}(I_i, \text{species})$$

3.1.2 Sum Rule:

Instead of taking the maximum of the scores from multiple organs, Sum rule takes the addition of the scores of the two organs as a single fused score.

$$\text{score}(q, \text{species}) = \sum_i^n \text{score}(I_i, \text{species})$$

3.1.3 Product Rule :

As the name suggests, Product rule takes the product of the scores from multiple organs to determine the fused score. However, Product rule is based on the statistical independence of the representations. This assumption is justifiable since, the observations of different single organs (such as leaf, flower, etc) are mutually independent.

$$\text{score}(q, \text{species}) = \prod_i^n \text{score}(I_i, \text{species})$$

3.2 Classification-Based Approaches

Another type of fusion technique is the classification based technique. Here, unlike the transformation-based technique, the confidence scores are concatenated into a single feature one dimensional vector, which then can be used as input to a binary classifier or a multiple class classifier. In this seminar, we have adopted the works in [6] which utilises a classification-based approach for fusing a variety of human gait features.

3.1.3 Support Vector Machine Based :

A SVM classifier, is trained by utilising both positive and negative training samples in the score space, where positive/negative samples are defined as a pair of scores at the corresponding true/false position of the species. Positive and Negative sample are selected as shown in Fig 3.

For a set of branch and leaf images, the positive and negative sample distribution, obtained from their individual confidence scores is provided in Fig 2.

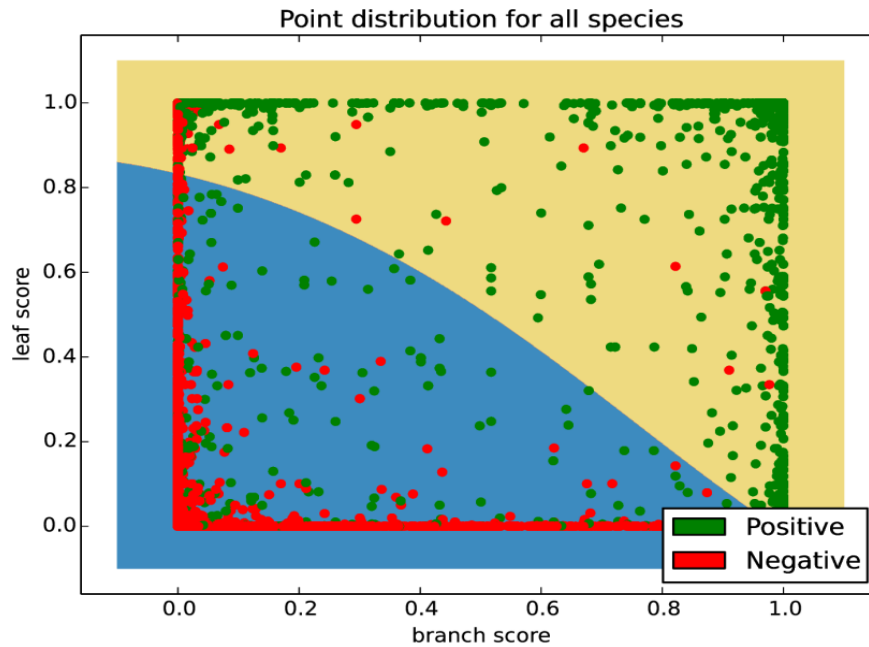


Figure 1: Distributions of negative and positive samples formed based on the branch and leaf scores

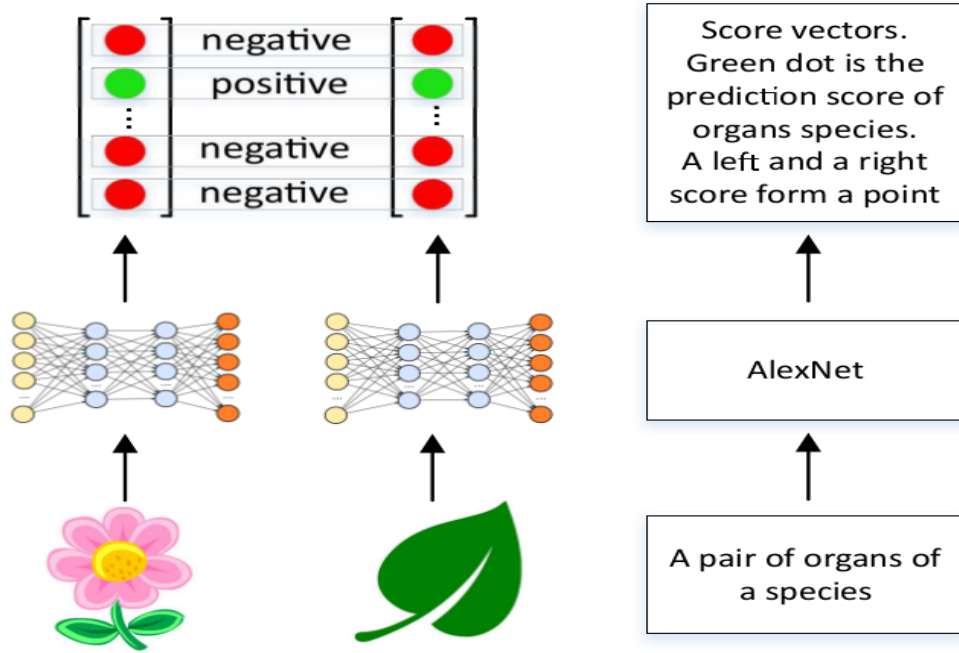


Fig. 3. Explanation for positive and negative samples

During the testing phase, after giving an input as a pair of organs to the CNN model, we have a pair of corresponding confidence scores. We then split the model into ‘n’ pairs where ‘n’ corresponds to the number of species. Then, we provide the splitted model as an input to the SVM classifier, and we store it if it comes out to be a positive sample. The species of the positive sample, which has the maximum distance to the decision bound, is the final label of the pair of organs.

4 EXPERIMENTAL RESULTS:

4.1 Collecting the dataset:

The above mentioned fusion strategies are evaluated with four types of plant organs namely, leaf, branch, flower and entire. For achieving a higher accuracy, it is necessary that the CNN is trained over a large dataset. Moreover, for ensuring higher prediction accuracy for multi-organ plant identification, it is necessary that multiple organ images of the same species are available. The difficulty faced while collecting data is the fact that even with a large dataset like that of PLANTCLEF 2015, there are only 12.5% observations with at least two organ images.

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				

Thus, for dealing with the above mentioned difficulty, we have deployed the following data retrieval schemes in this seminar. PlantCLEF 2015 dataset is one of the largest dataset of plant species in the world. As a result, we first extract the most common species having the largest number of images, similarly followed by 49 such species having the highest number of observations. We used Bulk Image Downloader, which is a powerful tool for collecting images on the internet using the species' name. The details of our final evaluation are shown in Table I.

The collected dataset is divided into three parts in the ratio of 5:3:2. The first part consists of the training dataset which is utilised for CNN for single organ identification. The third part is used for testing the CNN model for accuracy, i.e., to evaluate the CNN for its performance. For fusion based on classification based approaches, to deploy the SVM classifier, the results from the second part of the dataset returning from CNN is used as a training dataset for the SVM model.

For balancing the number of positive and negative samples, instead of taking all of the negative samples, we randomly collect the negative points.

4.2 Experimental Results :

The main outcome generated from our experimentations proved that the accuracy generated by using fusion strategies are better as compared to the model where single organ images are utilised.

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

From the above observations, we can see that the highest accuracy obtained using single organ images turned out to be 73% when flower was used to identify the species.

Similarly, as shown in Table III, by applying the above mentioned fusion strategies on a combination of two organ images from a set of leaf, branch, flower and entire, the accuracy rate increases dynamically between 16.8% to 90.8% .

Thus, from Table II and Table III, we can clearly see that the accuracy provided by the training a model using fusion strategies turned out to be better as compared to a single organ image based model. Moreover, in all of the six pairs of multi organs combinations, the product rule fusion strategy showed the best accuracy amongst other fusion strategies.

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

Figure 2: PR means Product Rule. The result of RHF and MC are put up as references only because of the variation in evaluation environments.

5 CONCLUSION AND FUTURE ENHANCEMENT

5.1 Conclusion

In this seminar, we examined various fusion schemes for identification of plant species using single as well as multi-organ plant images. From the experiments conducted above, it was shown that fusion schemes provide more accuracy as compared to single organ plant species in identification of plant species.

5.2 Future Enhancements

- In future work, we attempt to deploy a model which identifies species by fusing together more than two organs (three organ image based). Moreover, generally in an image of plant there are usually more than one organ present. Thus, to further enhance our CNN model, we would be automatically identifying the species from the image for fusing their confidence scores.
- By combining the above mentioned tasks, we support the end-user, like farmers, getting high performance without caring about the type of organ actually present.

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APPENDIX – D

Log Book

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Name of the Student :- Shantanu Jain

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Seminar Title :- Identification of Image-Based Plant Species using Single and Multiple Organ Images

Sr. No.	Date	Details of Discussion/ Remark	S Signature of Guide/ S seminar In charge
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Student Signature

Guide Signature