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A Novel Approach For Multi-Organ Plant Classification Based On Artificial And Convolutional Neural Network

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Abstract: *To Classify the plants based on a multi-organ approach is very challenging. The additional data provides more information that might help to disambiguate between species, the changeability in shape and appearance in plant organs also raises the degree of complexity of the problem. The prior approaches focus mainly on generic features (shape,size,color) for species classification, disregarding the features representing plant organs. we introduced a Hybrid Generic Organ Convolutional Neural Network (HGO-CNN), which takes into account of both organ and generic information, merging them using a new feature fusion speculation for species classification. Instead of using a ANN based method to operate on one image with a single organ, we extend our approach. We propose a new framework for plant structural learning using the Convolutional Neural Network(CNN) and recurrent neural network (RNN) . Based on feature visualization techniques here we depicts the outcomes of visualizations of our hypothesis.*

Index terms: *Deep learning, plant classification, Artificial neural network, CNN.*

I. Introduction:

Biodiversity generally refers to variety and variability of earth. according to the United Nations Environment Programme (UNEP), biodiversity typically measures variation at the genetic, species and ecosystem level. To protect biodiversity, people have begun building knowledge of accurate species to recognize unknown plant species. Taxonomists, botanists, and other professionals determine plant species from field observation based on a substantial species knowledge gained through their field work and studies. Categorization of plants still remains a tedious task due to limited knowledge and information of world's plant families. For this reason, taxonomists started seeking methods that can meet species identification requirements, such as developing digital image processing and pattern recognition techniques.

Recent progress in computer vision makes it possible to assist botanists in plant identification tasks. The majority of computer vision approaches utilizes leaves for discrimination, as leaf characters have been predominantly used to clarify plants. Characters such as shape, texture and venation are the features most generally used to distinguish leaves of different species. Nevertheless, due to the intra or interspecies diversity of plants in nature, some species are difficult or impossible to differentiate from one another using only the leaf organ. In fact, this ambiguity occurs also in other organs.

Using solely a single image of a fruit organ makes it considerably hard to differentiate between species, especially for non-botanists who have limited knowledge of plant characters. However, if we extend our observation to multiple organs such as branches and leaves, together with fruits, we can easily find out that they have discriminative patterns, as a significant cue for plant recognition. For example, the differences between the appearance of branches as well as the venations of leaves.

II. Proposed work

The proposed system has two frameworks to classify different plant organs images. First, we present a novel CNN architecture called the hybrid generic-organ convolution neural network, abbreviated HGO-CNN. Specifically, it extracts prior organ information, and, classifies one image based on the correlation between the chosen organ and generic-based features. Second, we propose a new framework of plant structural learning based on recurrent neural networks (RNN), namely the Plant-StructNet. Specifically, it takes in a varying number of plant views images composed of one or more organs, and, optimizes the contextual dependencies between them for species classification. To summarize our major contributions.

We present two novel plant classification frameworks, namely the HGO-CNN and Plant-StructNet. The HGO-CNN can be seen as a per-image modeling focusing on feature representation of one image capturing a single plant view (or organ), while the Plant- StructNet can be as a multi-image modeling that operates on multiple plant views capturing one or more organs of a plant.

We experimentally show that modeling the dependencies between plant views can essentially improve the performance of plant classification. In addition we demonstrate that the ensemble model combining the enhanced HGO-CNN and Plant-StructNet architectures outperforms the state-of-the-art (SOTA) on the Plant-Clef2015.

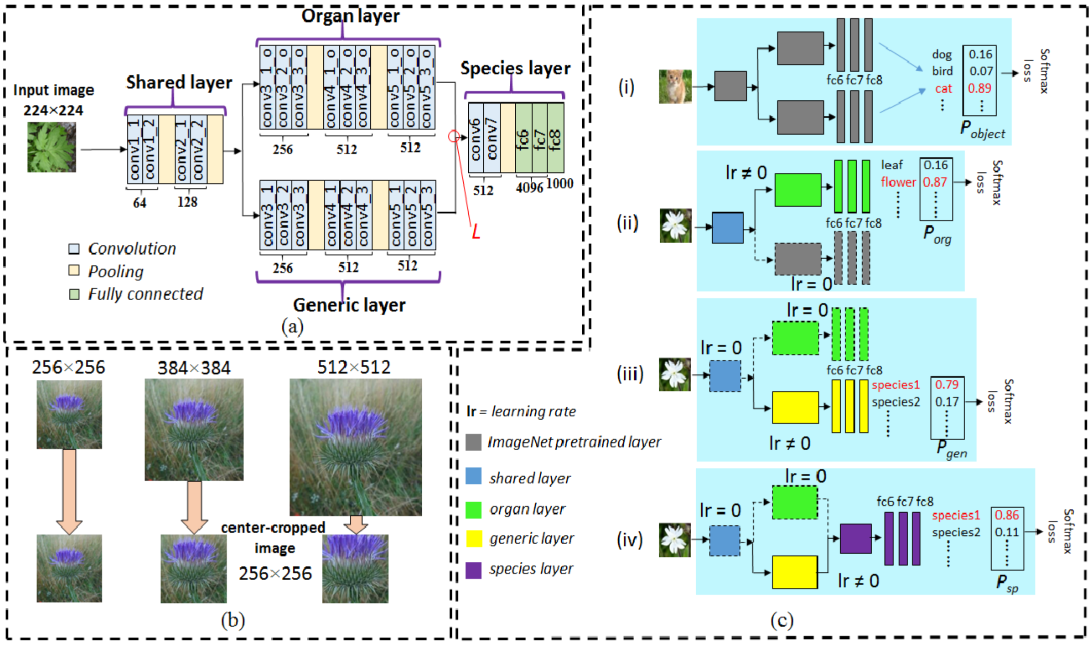

Fig:1 Block diagram of HGO-CNN

HGO-CNN Architecture :It is contains the four types of layers or components. They are shared layer, organ layer ,generic layer, species layer.

Pre-Training CNN layers : HGO-CNN uses a two-path CNN .For the purpose of training generic and organ based features at a later stage. This two path CNN is similar to the architecture depicted except that, it does not include the interconnection between paths, and each path has its own fully connected layers. These are initially pre-trained using the Image Net challenge dataset.

Organ layer : After we obtained the pre-trained two-path CNN, one of the CNN paths is repurposed to extract organ features. This organ layer is trained together with the shared layer, using seven kinds of organ labels predefined in the PlantClef2015 dataset. The organ labels are branch, entire, flower, fruit, leaf, stem and leaf scan. We train the shared layer based on the organ labels is because the shared layer that corresponds to the low-level features is more appropriate to be trained upon the course-level organ classes instead of the class-specific species classes. So that, it can be more generalised to fit in the modeling of both target classes.

Generic layer: After training the organ layer, another CNN path is repurposed to extract the generic features. This generic layer is trained using the 1000 species labels predefine in the PlantClef2015 dataset, regardless of organ information. We obtain generic-based feature maps. To allow both the organ and generic layers to share the common proceeding layer, we keep the shared layer's weights to be consistent. This is achieved by setting their learning rate to zero.

Species layer : To introduce correlation between both the organ and generic components .The feature maps ycat will then go through convolution layers to learn the combined representation of generic and organ features. Since these two convolution layers are new randomly-initialised, we set their learning rate to be 10 times higher than the other layers during tranning.

CNN architecture:

A convolutional neural network is a class of deep, feed-forward artificial neural networks, most commonly applied to analyzing visual imagery. Convolutional networks were inspired by biological processes. The network learns the filters that in traditional algorithms were hand-engineered. They have applications in image and video recognition, recommender systems and natural language processing.

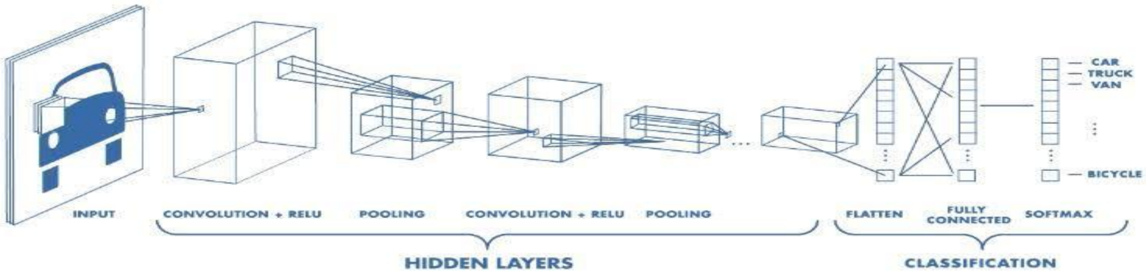

Fig:2 Architecture of convolutional neural network.

A.Convolution*:* A filter image(e.g line detector) examines every location of the input image to search for a line. If it detects a line, the filter will be activated. It will move one unit to the right until it reaches the end of the input image. Every location is recorded in an array called the feature map. Locations that have a line will have a high value and those that are not will have a value of zero.
B. Max pooling: A type of pooling layer which reduces the size or resolution of the incoming input layer. By doing so, the computation cost is reduce significantly and over fitting is avoided.
C. Fully Connected Layers: This layer is located at the end of the network. It connects all the activated location in every layer preceding it. Its output is an N dimension vector where N is the number of class that the network is trained to classify—in our study we have 5 classes. Each element in the vector contains the probability that the object belongs to the class. The element with the highest probability is the classification result.

PARAMETER MEASUREMENT
ROC curve: It is a fundamental tool for diagnostic test evaluation. In a ROC curve the true positive rate (Sensitivity) is plotted in function of the false positive rate (100-Specificity) for different cut-off point of a parameter.
Sensitivity: True positive rate(TPR) or Sensitivity Represents the percentage of samples which actually belongs to the class and identified as such. The formula is shown in (1).

$$TPR = \frac{TP}{TP + FN}$$

Specificity: Specificity or True Negative Rate (TNR) represents the percentage of the samples which actually don't belong to the class and identified as such. The formula is shown in (2).

$$TPR = \frac{TN}{TN + FN}$$

Accuracy: The accuracy of a test is its ability to differentiate the input images and classified cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and negative in all evaluated cases. Mathematically, this can be stated as (3).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Confusion Matrix: A confusion matrix (or error matrix) is usually used as the quantitative method of characterizing image classification accuracy. Columns of table 1 are the ground truth classes, and rows of the table are the classes of the classified image to be assessed.

III. Result Analysis:

Fig : input image

fig : classified image

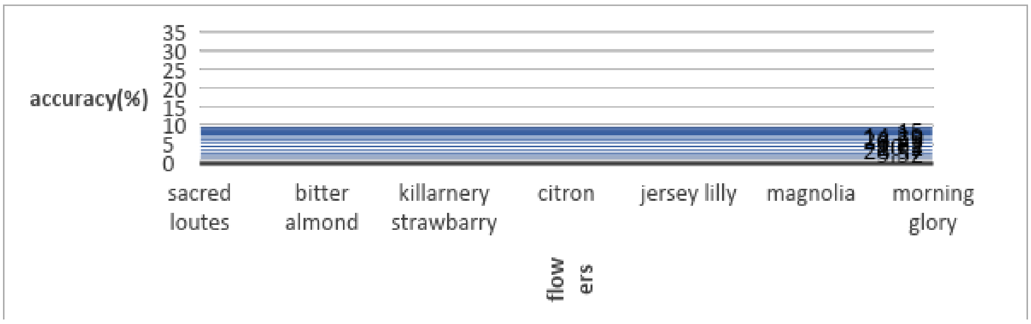

Fig : Performance of images that fall under category

Table1: performance of seven set of flowers using CNN

Flowers	Epoch	Iteration	Time elapsed(secs)	Min-batch loss	Min-batch accuracy(%)
Sacred lotus	1	20	12.80	2.639	9.52
Bitter almond	1	20	13.66	2.359	28.57
Killarney strawberry	1	20	7.57	2.6847	10.2
Citron	1	20	11.31	2.339	9.87
Jersey Lilly	1	20	14.38	2.339	28.82
Magnolia	1	20	12.67	2.7416	14.29
Morning glory	1	20	12.65	2.0990	14.52

IV. Conclusion:

HGO-CNN which uses an end-to-end deep neural network to integrate both organ and generic features, and, capture the correlation of these complementary information for species classification; The Plant-StructNet which offers extra flexibility in learning the relationship between plant views and supports classification based on varying number of plant images captured from a same plant. It would be interesting to consider integration of both CNN and ANN based models in order to simultaneously handle rich visual representation learning and context dependencies modelling within a fully end-to-end deep network.

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