# Large-Scale Plant Classification with Deep Neural Networks

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## ABSTRACT

This paper discusses the potential of applying deep learning techniques for plant classification and its usage for citizen science in large-scale biodiversity monitoring. We show that plant classification using near state-of-the-art convolutional network architectures like ResNet50 achieves significant improvements in accuracy compared to the most widespread plant classification application in test sets composed of thousands of different species labels. We find that the predictions can be confidently used as a baseline classification in citizen science communities like iNaturalist (or its Spanish fork, Natusfera) which in turn can share their data with biodiversity portals like GBIF.

## **KEYWORDS**

deep learning, plant classification, citizen science, biodiversity monitoring

#### **ACM Reference format:**

Ignacio Heredia. 2017. Large-Scale Plant Classification with Deep Neural Networks. In *Proceedings of ACM CF'17, Siena, Italy, May 15-17, 2017*, 5 pages. DOI: 10.1145/3075564.3075590

## **1** INTRODUCTION

The deep learning revolution has brought significant advances in a number of fields [1], primarily linked to image and speech recognition. The standardization of image classification tasks like the ImageNet Large Scale Visual Recognition Challenge [2] has resulted in a reliable way to compare top performing architectures. Since the AlexNet architecture [3], the first efficient implementation of convolutional neural networks using GPUs, the error in these competitions has reached superhuman performance [4].

Despite this recent success in general image recognition, the work in the biodiversity community relies heavily on hand labeled image data assigned by a (relatively) small community of experts and does not exploit these recent advances. This might be an impediment to open the community to non expert users who, armed with modern technologies handily embedded in a smartphone, can push biodiversity monitoring to the next level. The use of deep learning for plant classification is not novel [5, 6] but has mainly focused in leaves and has been restricted to a limited amount of species, therefore making it of limited use for large-scale biodiversity monitoring purposes. This same specificity issue applies to some standardized plant datasets [7] which are very helpful to evaluate the network performances but who are limited in variety of species or in the diversity of the images (focusing mainly in flowers or leaves). The PlantNet tool [8, 9], based on distant versions of the IKONA algorithms, pioneered in creating an open access tool to automate the task of recognizing a wide variety of species. However it does not reach the performance of expert botanists. Applying the recent advances in convolutional neural networks could have a positive impact in closing this performance gap. This could be a large step towards building a reliable and general large-scale plant recognition app that spreads the use of citizen science for biodiversity monitoring.

## 2 THE DATASET

As training dataset we use the great collection of images which are available in PlantNet under a Creative-Common Attribution-ShareAlike 2.0 license. It consists of around 250K images belonging to more than 6K plant species of Western Europe. These species are distributed in 1500 genera and 200 families. Each image has been labeled by experts and comes with a tag which specifies the focus of the image, like 'habit', 'flower', 'leaf', 'bark', etc. Most images have resolutions ranging from 200K to 600K pixels and aspect ratios ranging from 0.5 to 2. The dataset is highly unbalanced because most labels contain very few images.

We train on the whole dataset (without making validation or test splits) as we intend to build a classifier trained on the same dataset as the PlantNet tool so that their performances can be fairly compared. Also we believe that testing the classification performance on a subset of PlantNet is not an accurate measure of the performance of the net on real-world data as all the images in the dataset are highly correlated (many photos inside a specie share author and are often taken from the same plant with slightly different angles). Therefore at test time we will use three external datasets to confidently measure the performance of our net.

## **3 THE MODEL**

As plant classification is not very different from general object classification, we expect that top performing architectures in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) would perform well in this task. Therefore we use as convolutional neural network architecture the ResNet model [10] who won the ILSVRC'15. This architecture consists of a stack of similar (so-called residual) blocks, each block being in turn a stack of convolutional layers. The innovation is that the output of a block is also connected with its own input through an identity mapping path. This alleviates the vanishing gradient problem, improving the gradient backward flow in the network and allowing to train much deeper networks. We choose our model to have 50 convolutional layers (aka. ResNet50).

As deep learning framework we use the Lasagne [11] module built on top of Theano [12, 13]. We initialize the weights of the

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ACM CF'17, Siena, Italy

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model with the pretrained weights on the ImageNet dataset provided in the Lasagne Model Zoo. We train the model for 100 epochs on a GTX 1080 for 6 days using Adam [14] as learning rule. During training we apply standard data augmentation (as sheer, translation, mirror, etc) so that the network never sees the same image. We do not apply rotation or upside down mirroring to the images tagged as 'habit', as it does not make much sense to have a tree or a landscape upside down. After applying the transformations we downscale the image to the ResNet standard 224×224 input size.<sup>1</sup>

## 4 EXPERIMENTS AND DISCUSSION

Our goal is to achieve a performance that we consider to be useful as baseline classification (ie. around 50% accuracy). However it is difficult to assess how our net performance compares to other existing algorithms for plant classification as the main competition for plant classification, PlantCLEF [15], uses datasets composed of images uploaded to PlantNet by users who might already be present in our training set. Therefore we have composed three test datasets with external photos.

To put the Resnet accuracy values into perspective, we will compare them with the performance of the PlantNet tool on these same three datasets. In the PlantNet tool you can upload an url, or an image from your local disk, along with a tag suggestion and it returns a list of suggested species. When assessing its performance we report the best predictions across all tags (ie. we suppose the user selects optimally the tag).

Finally for the ResNet50 evaluation we use random ten crop testing with smaller data augmentation parameters than those used during training.

#### 4.1 The datasets

4.1.1 Google Search Image. For this dataset we select the 3680 labels (around 60% of all labels) with more than 12 images in our training dataset. For each one of these labels we automatically retrieve the 10 first images returned by the Google Image Search engine. As this is done in an automated fashion some minor mislabeled or corrupt examples might appear in the dataset. By choosing only the most popular labels and retrieving the top results, we expect to minimize the presence of mislabeled images.

4.1.2 *Portuguese Flora.* The Portuguese flora dataset [16] consists in 23K images belonging to 2K species. To compose our test dataset we select the 15K images belonging to one of the 1300 species which are also present in our training dataset.

4.1.3 *iNaturalist.* iNaturalist is a website were the user can upload their observations, that can have one or several images, and get help from the community to have them correctly labeled. For composing our dataset we select only the observations with research quality grade (ie. a consensus has been reached in the community on the species or genus label). There are around 600K such plant observations belonging to several ranks like species (97% of the total), genus, variety, subspecies, hybrid, etc. Selecting the observations tagged as (pure) species we end up with 900K images belonging to 20K plant species. From this set of images we only select the ones belonging to any of our 6K training species and we

 $^1 Code \ is \ available \ at \ github.com/IgnacioHeredia/plant_classification$ 





### **Predicted labels**

- 1. Verbascum thapsus | 50%
- 2. Pinus sylvestris | 4%
- 3. Pinus pinaster | 2%
- 4. Pinus nigra | 2%
- 5. Verbascum pulverulentum | 2%

FIG. 1: Example of non-trivial image classification with the ResNet50. Here the true label is Verbascum Thapsus which is also the first predicted label.

Datasets	Accuracy %			
	ResNet50 (ours)		PlantNet (usual)	
	Top1	Top5	Top1	Top5
Google Search	40	63	18	37
Portuguese Flora	29	47	15	29
iNaturalist	33	49	18	30

Table 1: Accuracy results of the two algorithms for all three test datasets.

end up with as test set composed of 300K images belonging to 3K different species.

In a later stage we will see how the prediction accuracy improves with observations containing 2 images or more. For that we end up with a test set of 60K observations containing between 2 and 33 images belonging to 2600 species present in our training dataset. Large-Scale Plant Classification with Deep Neural Networks



FIG. 2: Detailed results for the iNaturalist dataset for observations containing from 1 to 4 images. a) Top1 (solid line) and Top5 (dashed line) accuracy as a function of the probability of the first predicted label. b) Proportion of observations that have to be discarded because they do not meet the desired confidence.

### 4.2 **Results and Discussion**

The ResNet50 returns a list of probabilities that each label is the correct label as shown in Fig 1. The top1 accuracy measures how often the correct label is the highest probability label, while the top5 accuracy measures how often the correct label is among the five labels with highest probability. Table 1 shows the top1 and top5 accuracy results for all three datasets. We can notice that the Resnet50 achieves  $\times 2$  and  $\times 1.7$  improvements for top1 and top5 accuracies consistently across datasets compared with the Plant-Net tool. The overall accuracy is approximately constant although slightly higher in the Google dataset probably due to higher image quality.

Although the accuracy results are better than those obtained with the PlantNet tool, they are far from being reliable enough to be systematically used to predict tags for all observations. One way to improve this is to only return an identification if the net is confident enough about its prediction. The Fig 2a shows how this accuracy improves when we only trust predictions who have a top1 probability above a certain cutoff. For example if we set the cutoff at 30% the top1 and top5 accuracies increase to 59% and 74% respectively. The value of the cutoff should be a trade-off between how confident we want to be and how many observations we are willing to discard. In Fig 2b we show the proportion of observations that had to be discarded because they did not meet the desired cutoff probability. In the case of setting the cutoff to 30%, we are discarding 55% of the observations.

But increasing the confidence cutoff is not the only way to improve the accuracy. Although observations with a single image are the majority (91% of the total) in the iNaturalist dataset, there are also observations with 2 (6%), 3 (2%), 4 (1%) and more images. If we use jointly those images to identify average the predictions of the observed specie we achieve much higher accuracies than with only one image due to the lower influence of random noise. For example if we examine again with the cutoff to 30%, we now have top1 accuracies of 75%, 80% and 84% for observations with 2, 3 and 4 images respectively. However the proportion of discarded images also increases compared to the 1 image case, reaching now 60%, 67% and 71%. ACM CF'17, May 15-17, 2017, Siena, Italy

Although one might argue that those multi image observations are a very small portion of the dataset (and therefore the improvement in overall accuracy marginal), it is important to notice the increasing trend of uploads of multi images observations in the recent times. For example in the last three months of 2016, the 1 image observations were merely 60% of the total whereas the 2, 3 and 4 image observations went up to 23%, 11% and 4% respectively.

In Fig 3a we show the confusion matrix of the iNaturalist test dataset predictions for observations with one image. We have ordered the species label in blocks of families and blocks of genera to unravel the inherent block structure of the matrix. As we can see, along the diagonal, which is densely populated as expected, there are blocks of different sizes which denote groups inside which confusion is frequent. Fig 3b zooms into one such a group where we can see that inside the family of Plantaginaceae, the species belonging to the genera Linaria, Plantago and Veronica are often confused with other species within the same genera. Another example of a typical block could be Fig 3c where we can see that the species belonging to the family are often confused with other species of the family irrespectively of their genus. Those three figures show that even when the net's confidence is high but the prediction is wrong, we will likely be able to extract useful information, either about the correct genus or either about the correct family. This can be valuable information for the users or experts to narrow the search of the correct specie.

Finally, with regard to a future deployment in the iNaturalist ecosystem, we have to note that those accuracy results are restricted to the species present in our training dataset who merely represent 30% of all plant species present in iNaturalist. This is due to the fact that we trained with just Western Europe species from PlantNet while iNaturalist receives observations from all around the world. This could be solved in future work by retraining the net with both the iNaturalist and all the PlantNet images (including South America, Indian Ocean and North Africa).

## 5 CONCLUSION

In this work we have built a large-scale plant classification algorithm based on the ResNet convolutional neural network architecture. We have evaluated the classification performance of our net on the observations of iNaturalist and obtained that we were able to classify almost half of these observations, who lied above a 30% predictive cutoff, with a top1 and top5 accuracies of 59% and 74% respectively. We have then demonstrated that the user ability to upload several images per observation (preferably of different plant parts or from different angles) critically improved the final accuracy. Finally we obtained that even when the prediction was wrong it was very likely that we could obtain some information about the true genus or family, so that it could be used by experts or users to narrow their search of the correct label.

In addition we have seen that trained with the same image dataset, the ResNet architecture outperforms the most widespread online public plant classification algorithm by around a factor of 2 in top1 and top5 accuracies. Besides our model does not require to enter a suggested image tag along with the observation.

With all this information in hand we think that large-scale biodiversity projects like the Global Biodiversity Information Facility



FIG. 3: a) Confusion matrix for the iNaturalist dataset of observations with 1 image. We zoom b) in a region where different genera as confused separately inside the same family and c) in a region where all the genera are confused inside the same family. We weight the counts in the matrix with the probability of the prediction. All columns have been normalized to 1. We plot only the 1.5K labels with more observations so that the matrix appears more dense.

Large-Scale Plant Classification with Deep Neural Networks

ACM CF'17, May 15-17, 2017, Siena, Italy

(GBIF) [17] or LifeWatch [18], the European research infrastructure on biodiversity, could very well benefit from this new techniques to build a fast and reliable method to automatically monitor biodiversity. This tool can definitely open the field to active contributions of non expert users including citizen scientists.

For future work there are several ways to explore how to achieve an increase in accuracy. The most obvious way is to increase the training dataset size. It should be noted that iNaturalist contains even more images than PlantNet so when training a net for deployment one should combine both datasets to increase the predictions accuracy. Here we trained with just the PlantNet dataset so that the comparison of performance with the PlantNet tool would be fair. The other way is to implement architectural modifications to the net that lead to a better generalization error. Along this line two promising variants of the Resnet architecture have recently appeared. The first one is the Stochastic Depth Network [19] in which we remove randomly some residual blocks during training, allowing the net to be more robust for generalization and to train deeper networks. The second more promising variant is the DenseNet [20] in which the skip identity connections are now connecting the residual blocks at all scales. Lastly it is worth mentioning that the Resnet50 is a quite space-consuming architecture so if we were to implement plant recognition app in embedded devices, so that the user could identify without connecting to the Net, one could use some recent modifications of shallower architectures that offer almost as good performance with much less memory consumption [21].

# ACKNOWLEDGEMENTS

I want to thank Jesus Marco de Lucas and Fernando Aguilar for their helpful comments and supervision. I also wanted to thank PlantNet and Flora-on for their image's open access policy, and the EGI-Engage Lifewatch Competence Centre for their support. The author is funded with the EU Youth Guarantee Initiative (Ministerio de Economia, Industria y Competitividad, Secretaria de Estado de Investigacion, Desarollo e Innovacion, through the Universidad de Cantabria).

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