Variable Complexity Neural Networks Comparison for Pollen Classification

Aysha Kadaikar, Yan Pan, Qiaoxi Zhang, Patricia Conde-Cespedes, Maria Trocan, Frédéric Amiel and Benjamin Guinot

Abstract—This paper deals with the problem of classifying the pollen grains observed in a microscope view acquired by a collector of ambient air particles. This classification is usually performed by a highly skilled human operator observing the microscope slide to detect the presence of pollen grains, count them and sort them according to their taxa. However these tasks become particularly heavy in the mid-season because of the huge quantity of pollen produced. This paper compares the use of three neural networks (NN) to classify the pollen grains observed which are a modified version of LeNet5, ResNet50 and AlexNet. The first two have been conceived more for non-natural images and the last one for natural images. Simulation shows that ResNet50 and AlexNet particularly lead to good performance in terms of accuracy for this kind of images. AlexNet is finally a good compromise for pollen classification when adding a constraint on the computational complexity.

Keywords—Neural networks, LeNet5, ResNet50, AlexNet, pollen classification, complexity.

I. Introduction

INTEREST on pollen analysis has been growing in the last decades as it is used in many fields. For example, in palynology as in paleopalynology, the pollen samples collected from the air, water or segments of any age are studied. Thus, the palynologist can have an idea on the vegetation and reconstruct the environment that produced those samples or make climate change studies [1], [2]. Another main application of pollen analysis consists in allergy prevention. In fact, about between 10 and 25 % of the world population suffers from allergic rhinitis [3]. And pollen is one of the primary caused of allergic rhinitis.

In this case, pollen analysis allows detecting the presence and the quantity of pollen in real time to prevent allergic reactions. Most commonly, pollen analysis is performed by a human operator using a captor dedicated to the collection of particles present in the ambient air. The captor runs all day long, day after day, and collects the particles on a moving ribbon. A person having high skills on pollen recognition finally analyzes the particles collected on the ribbon with a microscope. One difficulty of the analysis consists on the variety of the particles present in the ribbon. Indeed, the pollen grains are found next to other particles such as pollution particles, soot, vegetal residues, water droplets etc... All of these constitute noise for the pollen analysis. An example of a microscope view containing pollen grains with noise is given in Fig. 1 where pollen grains have been colored in purple. Another difficulty of the pollen analysis consists in the huge number of pollen to count and classify. These tasks can become particularly difficult in the mid-season when the number of pollen grains explodes. Finally, the classification of the pollen samples is a difficult task, which requires a highly skilled person to detect the features of each type of pollen and classify them according to their taxa. Fig. 2 gives an example of different types of pollen to classify.

In recent years, some studies have been conducted to automatize the tasks of analyzing pollen grains present in the ambient air in real time. In [4], the authors propose to use autofluorescence image analysis. For this, a digital camera capturing autofluorescent images of pollen in real time is placed inside a device dedicated to the collection of pollen particles. The pollen are classified according to their level of blue and red spectra. In [5], the authors also use fluorescent images to classify the pollen samples with an approach based on the pixel intensities of the images. Although these methods could lead to good classification performance, the material used is costly and make difficult a wide deployment of these methods.

In this paper, we propose to automatize the task of classification of the pollen samples detected on a microscope view in real time. For this, we have compared the usage of three neural networks to classify the pollen grains. Two of them are dedicated to non-natural images and the last one is dedicated to natural images. The rest of the paper is organized as follows. The next section presents the three neural networks we have compared for the classification. Section III compares the performance of the algorithms according to their performance and complexity. And finally, Section IV concludes this work.

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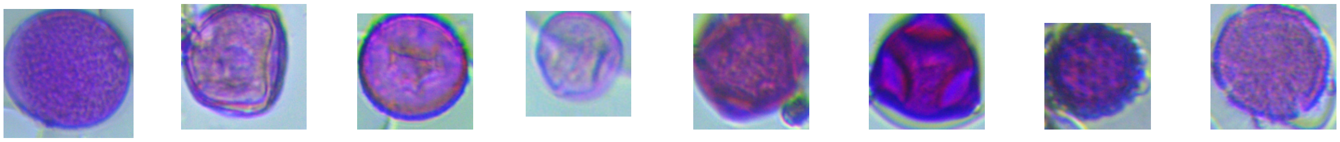
Manuscript received May 5, 2019.

II. Comparison of three neural networks

For this application of classifying the pollen grains, we have tested three neural networks amongst all existing to compare their performance. Each of them has been conceived for a defined type of images (natural or non-natural) and they are of different complexity. Let us present the networks used for the tests.

A. Modified LeNet5 neural network

As one of the earliest Convolutional Neural Network (CNN), LeNet-5 is the commencement for a large number



(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 2: Overview of different pollen grains. (a) Poaceae (b) Populus (c) Cupressaceae (d) Urticaceae (e) Betulaceae (f) Corylus (g) Ambroisie (h) Fraxinus

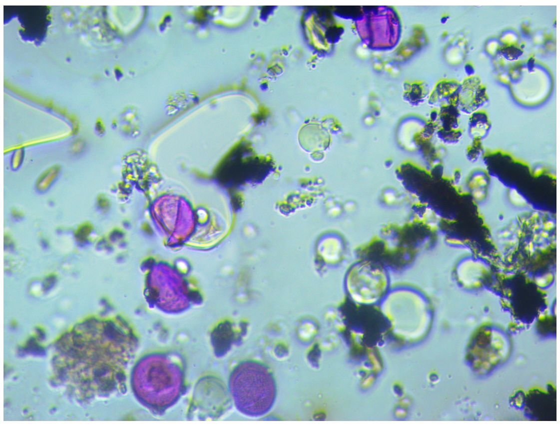


Fig. 1: Example of a microscope view

of recent neural network architectures, bringing a lot of inspiration to this field [6]. LeNet-5 extracts features using convolution, parameters sharing, pooling and other features avoiding a lot of computational costs. However, when it comes to complex ubiquitous object as well as medical micrograph images, the original network structure working on MNIST dataset is far from meeting the requirement. LeNet5 has shown to be very performing in the case of non-natural images, especially for handwritten digits recognition [7], [8]. The version that has been tested here is mostly inspired by LeNet5 but is a bit different [9]. It is called Modified LeNet5 in the rest of the paper. It is composed of 9 layers including 2 convolutional layers, 2 sub-sampling layers (or pooling layers), 2 Local Response Normalization (LRN) layers and one fully connected layer. These layers are summarized in Fig. 3. The first convolution layer filters the 208×208 input image with 16 kernels of size 3×3, and the stride of the sliding window for each dimension of the input tensor is 1, which means every pixel on each channel is scanned. A filter summarizing the outputs of neighboring neurons from the previous layer performs pooling layer after the convolution layer. The obtained output has smaller height and weight dimensions but the same depth as the previous tensor. After the pooling layer, a local response normalization is applied performing a kind of lateral inhibition by making a normalizing over local input regions. The second convolution layer is similar to the last convolution, but the channel of kernels change to 16 because of the output of previous layers and the LRN is applied before the pooling layer. At the third fully connected layer, the results from those two convolution layers are flattened, and the weights and biases are initialized, preventing overfitting of fully connected layers.

B. Resnet50

Residual neural network (ResNet) is one of the pioneering productions for deep learning in recent years. The emergence of ResNet has made it possible to train hundreds or even thousands of layers of neural networks, and the results of training are also remarkable. This kind of networks are very generally used on non-natural images (such as medical images) and has shown very good classification performance [10], [11]. As known, the depth of the network is crucial to the performance of the model. When the number of network layers is increased, the network can extract more complex feature patterns, thus better results can be obtained. However, degradation problem occurs in deep networks, causing the saturation or the decrease of the network accuracy. The author of the ResNet, Kaiming He, proposed an effective solution, addressing this problem by introducing a deep residual learning framework, which shows better performance by utilizing skip connections, or shortcuts to jump over some layers. The version we have tested in this paper for the pollen grains classification is ResNet50 [12]. This is one of the most powerful and relatively simple-structured ResNet variants with 49 convolutional layers and one fully-connected layer. The convolutional layers are designed to make sure every layers output feature map sizes are the same, and to preserve the time complexity per layer. Downsampling is performed by convolutional layers with a stride of 2, and the residual structure is built by inserting shortcuts. Moreover, 3-layers bottleneck blocks are designed and applied to shorten training time. The three layers are 1×1, 3×3, and 1×1 convolutions. The 1×1 layers reduce and then increase dimensions, thus 3×3 layer can process input and output data with smaller dimensions, which makes the model more efficient. At last, the network ends with a global average pooling layer and a 1000-way fully-connected layer with softmax. Fig. 4 gives an overview of the residual network we have tested in this paper.

C. Alexnet

The third neural network we have tested is AlexNet. Indeed, this neural network achieves very good classification performance in the case of natural images as it was the case in the ImageNet LSVRC-2012 contest which made this network

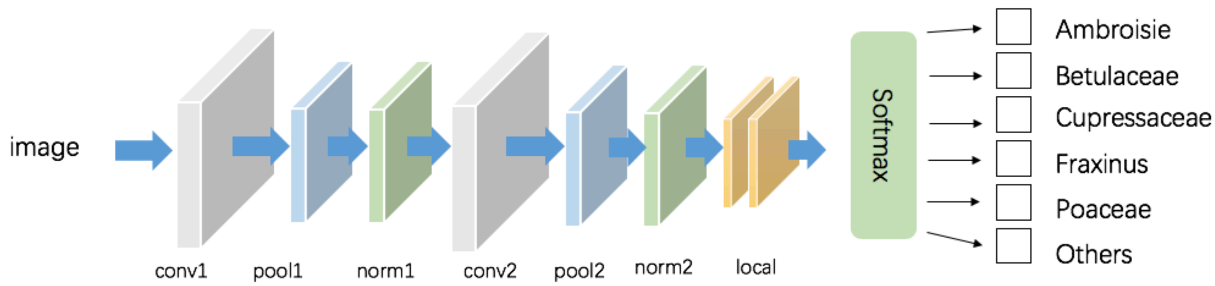


Fig. 3: Topology of the Modified LeNet5 network.

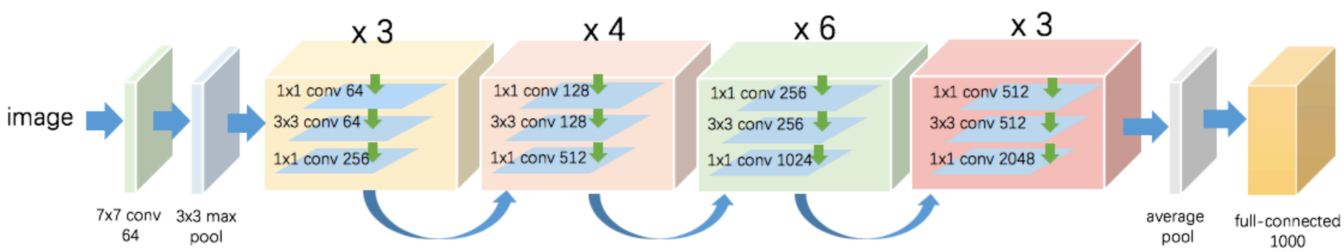


Fig. 4: Topology of the ResNet50 network.

famous [13]. It is more computationally complex than LeNet5 but much less than ResNet50. When AlexNet was developed, it was deeper than already existing CNN. It has more than 60 million parameters and more than 650, 000 neurons. The architecture is similar to the one of LeNet whereas AlexNet is deeper, has many kernels per layer and presents successive convolutional layers. More precisely, AlexNet is composed of 5 convolutional layers and 3 fully-connected layers as shown in Fig. 5. An OverLapping Max Pooling layer directly follows the first two convolutional layers, and then there are two successive convolutional layers followed by an OverLapping Max Pooling layer again. And finally the output of the previous layer is connected to three successive fully-connected layers where the last one is a classifier with 1000 class labels.
AlexNet also includes many tools as max pooling, dropout, data augmentation, ReLU and SGD with momentum.

III. Experimental Results

This section presents a comparison of the performance of the three neural networks used to classify the pollen grains. Tests have been conducted on a dataset composed of 1200 images of different pollen acquired using the HCA-algorithm described in [14]. The dataset is composed of 6 classes including the 5 most allergenic and most abundant type of pollen, i.e. the Poaceae, the Cupressaceae, the Ambrosia, the Betulaceae, and the Fraxinus (see Fig. 2). The sixth class is composed of all other existing pollen that have been encountered making the dataset (it contains Pinus, Urticaceae, Corylus, Alnus, etc...). Each class contains around 200 images. The first section describes the test parameters of each neural network. Then the next section discusses the performance of the neural networks in terms of accuracy and finally, the last section discusses the performance in terms of computational complexity and time consumption.

A. Parameters of the neural networks

We present here the settings of the parameters of the networks.
Concerning the Modified LeNet5, the batch-size is set to 10 images, the number of epoch is equal to 5000, the capacity of the network is set to 1500 and the learning rate is set to 0.0001.
For ResNet50, the batch size is taken as equal to 32, the number of epoch is equal to 50 and the learning rate is set as 0.01. Finally for AlexNet, the mini batch size is set to 64 images, the learning rate is set to 0.001, and the maximum epochs number is equal to 20.

B. Classification performance

This section presents the performance of the three neural networks that have been trained and tested with the dataset presented above. Tab I gives an overview of the results with three different ratios of number of images for the training and the test. More precisely, we have tested the following ratios (training/test) in percentage: 70/30, 80/20 and 90/10.

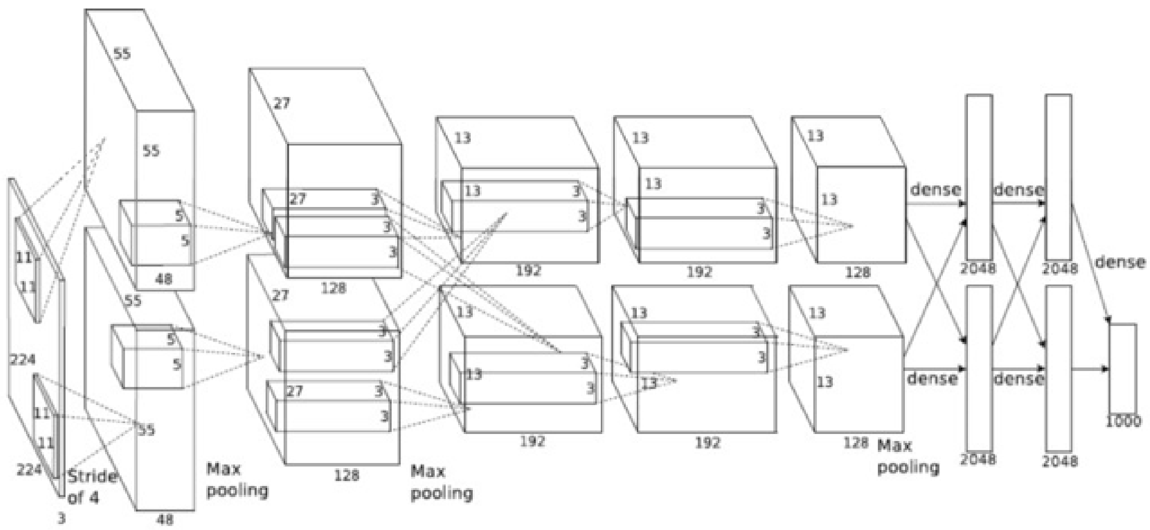


Fig. 5: Topology of the AlexNet network.

TABLE I: Classification performance of the three neural networks

Ratio training/test	LeNet	Resnet	Alexnet
70/30	85.35	96.54	96.01
80/20	87.26	96.81	96.02
90/10	86.52	97.60	94.40

One can see that ResNet50 and AlexNet achieve much better performance in terms of accuracy than the modified LeNet5. Detailed results of the three algorithms are given in Tab II to Tab IV.The provided results show the estimated labels after classification versus the original labels of the images using 80% of the total amount of images for the training and 20% for the test. The diagonals of the tables contain the ratio of true positive for each class (in percentage). One can see that the three algorithms have very good performance on most of the classes with still an advantage for ResNet50 and AlexNet over the modified LeNet5. Classification accuracy is lower for the class ”Others” in particular. This is due to the great heterogeneity of this class containing only a small amount of very different varieties of pollen contrarily to the others classes which contain many images of the same type of pollen. So the training is better performed in the latter case.

Fig. 6 to Fig. 8 show the ROC curves associated to the class ”Ambrosia” for the three algorithms. The Aera Under the Curve (AUC) is very close to 1 in all cases. In the same way, Fig. 9 to Fig. 11 present the ROC curves associated to the class ”Others” for the three algorithms. The AUC is a bit lower than previously because of the difficulty of the training due to the heterogeneity of this class as explained earlier. For the other classes, as it is the case in these examples, the AUC of the ROC curves for the three algorithms are very close to 1. Globally, Resnet50 achieves slightly better performance than Alexnet which is also more performant than the modified LeNet5.

In regards to all the performance results, it appears that both ResNet50 and AlexNet which has been designed for natural images, offer very satisfying results in terms of accuracy. On the other hand, the modified Lenet5 which was developed for non-natural images is less performant in pollen grains recognition.

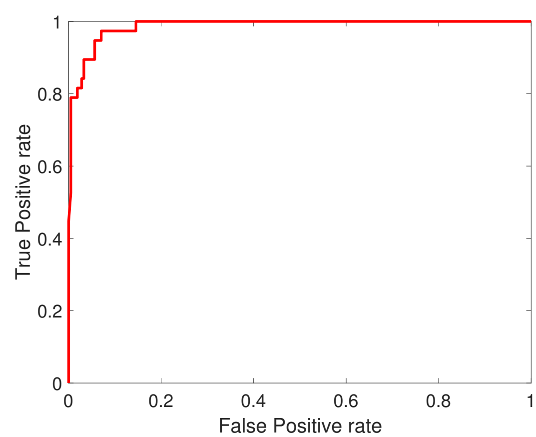


Fig. 6: ROC curve associated to the class **”Ambrosia”** with the **modified LeNet5** (AUC = 0.9870).

C. Comparison of the complexities and processing times of the neural networks

This section discusses the computational complexity and the processing time of each neural network.

The Modified LeNet5 version used in this paper contains a little more than 1 million learnable parameters and need about 19.5 million mutliply-add operations to compute the parameters for a single image [9]. Alexnet computes around 60 millions of parameters and needs about 700 millions of operations to compute them for one image. And finally, ResNet50 contains 25.6 million parameters but it needs around

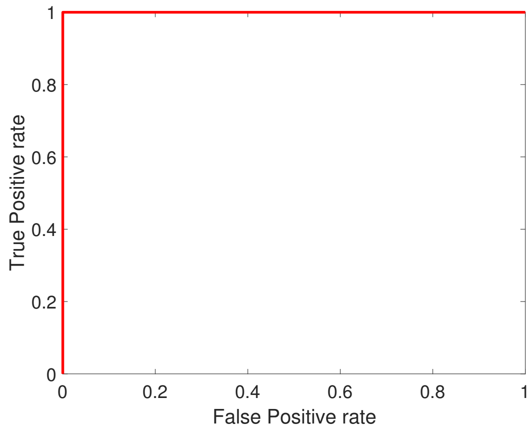


Fig. 7: ROC curve associated to the class **”Ambrosia”** with **ResNet50** (AUC = 1).

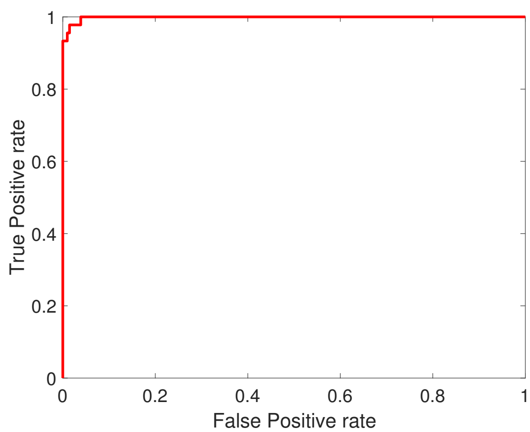


Fig. 8: ROC curve associated to the class **”Ambroisie”** with **Alexnet** (AUC = 0.9948).

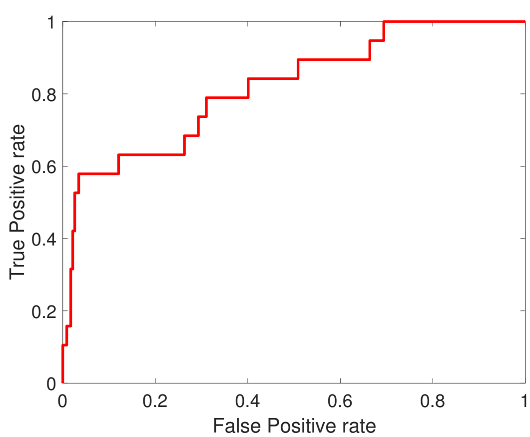


Fig. 9: ROC curve associated to the class **”Others”** with the **modified LeNet5** (AUC = 0.8187).

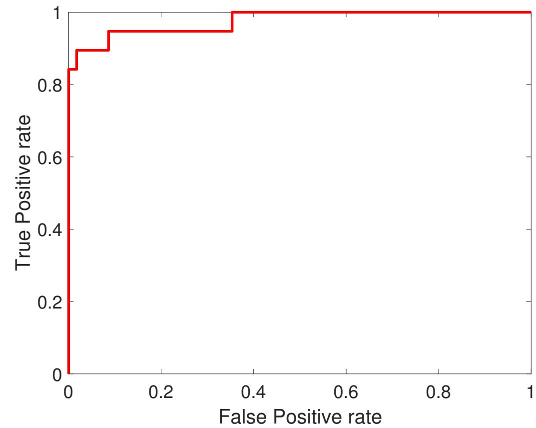


Fig. 10: ROC curve associated to the class **”Others”** with **ResNet50** (AUC = 0.9760).

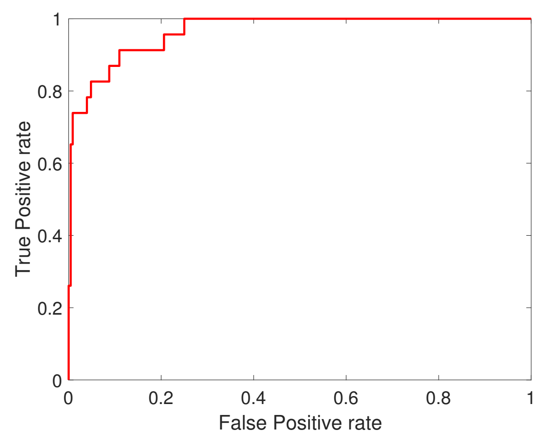


Fig. 11: ROC curve associated to the class **”Others”** with **Alexnet** (AUC = 0.9653).

8 billion operations for the parameters computation for one image. ResNet50 is far more complex than the modified LeNet5 and AlexNet.

Let us now have a look on the processing times of the algorithm. The modified LeNet5 and ResNet50 have both been tested on the Google collaborative platform with Python (version 2.7) and TensorFlow (version 1.13.1). The training of 80% of the dataset took about 653 seconds for the modified LeNet5 versus 1300 seconds for ResNet50. In the same way, the test of the 20% remaining took about 9 seconds for the modified LeNet5 versus 2 seconds for ResNet50.

Alexnet have been run using a Macbook pro with an Intel Core i5 processor of 2.4Ghz and 4GB of RAM. The simulations have been done with Matlab (version r2018b). Considering the test with 80% for the training and 20% for the test, the algorithm takes 3867 seconds for the training and 57 seconds for the test.

Finally, having a look at the overall performance of the three neural networks, it appears that AlexNet seems to be a good compromise in terms of accuracy and complexity as compared to the modified LeNet5 and ResNet50. In fact AlexNet achieves excellent performance as ResNet50 in terms of accuracy but it is much less complex.

IV. Conclusion

In this paper we have compared three neural networks for the classification of pollen grains. Two of them have been originally conceived for non-natural images (LeNet5 and ResNet50) and the third one have been conceived for natural images (AlexNet). Simulations results has shown that for this application with pollen images, both ResNet50 and AlexNet lead to good performance in terms of accuracy with a preference for AlexNet in the case there is a constraint on the computational complexity.

Acknowledgment

The authors would like to gratefully acknowledge the support of the National Research Agency and the STAE foundation under the auspices of the Saint-Exupery Technological Research Institute without which the present study could not have been completed. The authors would like to address special thanks to Roland Sarda-Estève and Dominique Baisnée from the Climat and Environnement Sciences Laboratory (LSCE) for their material support. And finally the authors would like to express their gratitude to Gilles Oliver and Michel Thibaudon from the French Aerobiology Network (RNSA) for their great support in this project.

References

[1] K. A. Holt and K. D. Bennett, *Principles and methods for automated palynology*, New Phytologist, vol. 203(3), pp. 735-742, 2014.

[2] S. W. Punyasena, D. K. Tcheng, C. Wesseln and P. G. Mueller, *Classifying black and white spruce pollen using layered machine learning*, New Phytologist, vol. 196(3), pp. 937-944, 2012.

[3] J. Bousquet, P. Van Cauwenberge and N. Khaltaev, *Allergic rhinitis and its impact on asthma*, Journal of allergy and clinical immunology, vol. 108(5), S147-S334, 2001.

[4] K. Mitsumoto, K. Yabusaki, H. Aoyagi, *Classification of pollen species using autofluorescence image analysis*, Journal of bioscience and bioengineering, vol. 107(1), pp. 90-94, 2009.

[5] S. Johnsrud, H. Yang, A. Nayak and S. Waduge Punyasena, *Semi-automated segmentation of pollen grains in microscopic images: a tool for three imaging modes*, Grana, vol. 52(3), pp. 181-191, 2013.

[6] Y. LeCun, L. Bottou, Y. Bengio P. and Haffner, *Gradient-based learning applied to document recognition*, Proceedings of the IEEE, vol. 86(11), pp. 2278-2324, 1998.

[7] A. El-Sawy, E.B. Hazem and M. Loey *CNN for handwritten arabic digits recognition based on LeNet-5*, In International Conference on Advanced Intelligent Systems and Informatics, Springer, 566-575, 2016.

[8] N. Yu, P. Jiao and Y. Zheng *Handwritten digits recognition base on improved LeNet5*, In The 27th Chinese Control and Decision Conference, pp. 4871-4875, 2015.

[9] *Advanced Convolutional Neural Networks*, https://www.tensorflow.org/tutorials/images/deep_cnn. Date last accessed: 04.03.2019.

[10] L. Yu, H. Chen, Q. Dou, J. Qin and P.A. Heng *Automated melanoma recognition in dermoscopy images via very deep residual networks* IEEE transactions on medical imaging, vol. 36(4), pp. 994-1004, 2017.

[11] Z. Zhong, J. Li, L. Ma, H. Jiang and H. Zhao, *Deep residual networks for hyperspectral image classification.* In 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), pp. 1824-1827, 2017.

[12] K. He, X. Zhang, S. Ren, J. Sun, *Deep residual learning for image recognition*, In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778, 2016.

[13] A. Krizhevsky, I. Sutskever, G.E. Hinton, *Imagenet classification with deep convolutional neural networks.*, In Advances in neural information processing systems, pp. 1097-1105, 2012.

[14] A. Kadaikar, M. Trocan, F. Amiel, P. Conde-Cespedes, B. Guinot, R. Sarda Estève, D. Baisnée and G. Oliver, *Automatic pollen grains counter*, In the proceedings of BioSMART, 2019.

[15] Li, Ping, and J. Flenley, *Pollen texture identification using neural networks*, Grana, vol. 38.1, pp. 59-64, 1999.

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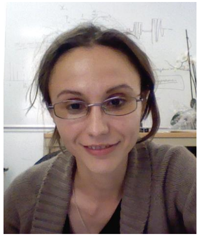

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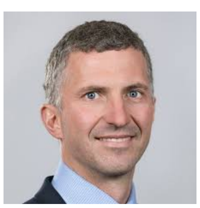

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For the past 9 years, Benjamin is the coordinator (PI) of monitoring observatory projects in China in close cooperation with the Chinese Academy of Sciences in Xian. He was granted the Chinese Academy of Science Young International Scientist Fellowship in 2011 and awarded the first price of the EU Science and Technology Fellowship China Program in 2012.

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TABLE II: Detailed performance of the modified **LeNet5**.

Original Labels \ Estimated Labels	Ambrosia	Betulaceae	Cupressaceae	Fraxinus	Poaceae	Others
Ambrosia	**95.8**	0	0	0	2.1	2.1
Betulaceae	2.9	**94.1**	0	3	0	0
Cupressaceae	0	1.8	**57.4**	16.7	14.8	11.1
Fraxinus	0	7	0	**78.9**	10.5	3.5
Poaceae	29.6	3.4	0	0	**62.1**	6.9
Others	10.7	32.1	9.2	7.1	10.7	**39.2**

TABLE III: Detailed performance of **ResNet50**.

Original Labels \ Estimated Labels	Ambrosia	Betulaceae	Cupressaceae	Fraxinus	Poaceae	Others
Ambrosia	**100**	0	0	0	0	0
Betulaceae	0	**98.6**	0	1.4	0	0
Cupressaceae	0	0	**100**	0	0	0
Fraxinus	0	0	0	**100**	0	0
Poaceae	0	0	0	0	**100**	0
Others	5.2	5.3	0	0	5.3	**84.2**

TABLE IV: Detailed performance of **AlexNet**.

Original Labels \ Estimated Labels	Ambrosia	Betulaceae	Cupressaceae	Fraxinus	Poaceae	Others
Ambrosia	**100**	0	0	0	0	0
Betulaceae	0	**100**	0	0	0	0
Cupressaceae	0	0	**100**	0	0	0
Fraxinus	0	0	7.2	**92.8**	0	0
Poaceae	12.5	6.2	0	0	**81.2**	0
Others	0	27.2	9.2	0	0	**63.6**