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Pollen Grain Recognition Using Convolutional Neural Network

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Abstract. This paper addresses two problems: the automated pollen species recognition and counting them on an image obtained with a lighting microscope. Automation of pollen recognition is required in several domains, including allergy and asthma prevention in medicine and honey quality control in the nutrition industry. We propose a deep learning solution based on a convolutional neural network for classification, feature extraction and image segmentation. Our approach achieves state-of-the-art results in terms of accuracy. For 5 species, the approach provides 99.8% of accuracy, for 11 species — 95.9%.

1 Introduction

The task of pollen recognition, that is to recognize plant species by its pollen, has roots in the field of palynology. Pollen analysis is applied for different purposes: honey quality control (identification of honey type and origin [1]), forensics tasks [2], etc. An important purpose comes from the medical domain, namely preventing allergy and asthma caused by pollens. Pollen has a huge impact on human health because it triggers off 90% of rhinitis that can turn into asthma without a treatment [3].

The harmful impact of hay fever can be reduced by designing an online system for notification about the start of the allergenic pollen dispersion. The existing approach for providing such information is based on the work of counting stations (about 600 stations in Europe), where palynologists manually recognize plant species by pollen grains catched from air in order to find allergenic ones. However, such manual analysis is too slow to provide relevant information for online systems and for patients. While the work on counting stations is almost pro-bono and imposes specific-purpose knowledge of biology, pollen recognition automation can dramatically reduce the required qualification level of operators as well as speed up the whole process. Using a visualization system, palynologists can easily take a screenshot of an image seen in the microscope, thus reducing

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the problem of automation to the automated pollen image recognition problem, which can be viewed as a machine learning task.

The goal of this paper is to suggest an approach for automated pollen detection, counting and recognition given digital images produced by microscopes. We propose to use a convolution neural network for classification and preprocessing of pollen species since this model has shown promising results in image processing and recognition [4].

The rest of the paper is organized as follows. The related works are overviewed in Section 2. Image preprocessing steps and deep learning model are described in Section 3. Dataset details are given in Section 4. The experiments are described and their results are presented and discussed in Section 5. Section 6 concludes the paper.

2 Related Work

The problem of automated pollen recognition was first stated almost 50 years ago [5]. Due to the recent success of machine learning algorithms in image processing and recognition, the problem is close to be resolved, but it is still interesting to researchers.

The first step in terms of machine learning is feature extraction. Most of the researchers who tried to resolve the problem used specific pollen features such as shape, size, brightness, texture features, aperture [6, 7, 8]. These features have clear semantics, but they are not universal.

After the features are extracted, classification methods are applied to them. Many researchers used standard machine learning classification methods. The results vary between 77% and 99% of accuracy [9, 10, 11, 6, 12, 13]. Many authors used images from a scanning electron microscope (SEM), which produces high quality images. It allowed to extract much more features and facilitates the classification task [6, 12]. But the SEM is at least 15 times more expensive than the lighting microscope. As the consequence, it is not widely used by counting stations. Some authors used z-stacks of multifocal images of one pollen grain as object for classification [6, 12, 13]. Despite this approach is effective and leads to high accuracy of recognition, it requires a large amount of pollen images. However, it is tedious for palynologist to make many images for each pollen grain in a real world application unless it is not automated. Thus, this automated recognition increases demand in manual pollen processing with microscopes.

Finally, an image may contain several pollen grains, which should be counted and segmented before the classification algorithms application stage. We call this process *pollen extraction*. However, this important step is ignored by many researchers.

In our previous research [14] we attempted to use GIST descriptors as image features instead of highly abstract features. GIST descriptors were chosen in order to provide independence from scaling and rotation. For the generated descriptors, we applied the a number of classification techniques to the different feature sets provided by dimension reduction methods. The best result was

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provided by SVM with a polynomial kernel applied to the features with the highest Mutual Information, the accuracy of which was 98.3%. The result was achieved on the preprocessed dataset.

According to the review of pollen recognition automation [15], some simple and common challenges related to pollen recognition already be addressed due to current technology stack, but many other problems are still unresolved such as recognition of broken, dried, deformed, clumped pollen.

3 Proposed Approach

3.1 Image preprocessing

To achieve the goal of pollen spectrum counting images should be preprocessed. This means the extraction of separate pollen grains, for which segmentation is required. Segmentation is usually applied to binarized images, i.e. black and white images. At the previous stage of the research [14] we used simple threshold binarization applied to hue and saturation channels. The result was satisfying, but the changes in microscope settings caused exposure changes, so that simple binarization cannot process image well enough. Therefore, we applied hypercolumn technique for binarization [16]. Hypercolumn is the vector of corresponding activations of one pixel of the initial image across all internal feature maps of CNN. Such approach is much more effective and provides better results than the standard computer vision techniques like threshold binarization and adaptive binarization.

The next step after binarization is segmentation. Initial images may contain multiple pollen grains, which can be clumped[1] making it hard task for image preprocessing.

There are two main kinds of segmentation: edge based and region based. In our previous work, we used only edge based technique – the Canny detector. The results were not good enough for the cases of clumped objects, extraction true positive rate was 73%. In this work we used region-based techniques and the mixed approach. The best result was provided by a marker-based watershed algorithm [17], which is a region growing technique. The example of the whole pollen extraction pipeline is shown in attachment[2].

3.2 Convolutional Neural Network Configuration

We performed grid search with the following search space: optimizer: Adam, Adadelta, Adagrad; kernel sizes: 5, 7, 9; dropout rates: 0.3, 0.5, 0.7; number of filters: 6, 10, 16, 20, 32; number of convolution layers: 3, 4, 5, 6; number of dense layers: 2, 3, 4; number of hidden units: 25, 50, 70, 100. After a series of experiments, we came to the following best network configuration and its hyperparameters (Figure 1), the kernel sizes were 7×7, 5×5 and 5×5, the activation function was ReLU. The optimizer we used was Adadelta.

[1] http://genome.ifmo.ru/files/papers_files/ESANN2018/clumped_example.eps

[2] http://genome.ifmo.ru/files/papers_files/ESANN2018/segmentation.eps

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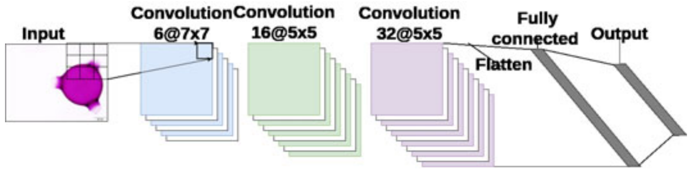

Fig. 1: Convolutional neural network configuration

4 Dataset

The dataset contains images obtained from a lighting microscope. It consists of 11 plant species pollen, 1774 images in total. The dataset is made using optical microscope Olympus BX51 with Olympus DP71 image viewing system.

Some examples of each pollen species are presented in attachment[3]. The table shows that pollen grain appearance within a taxon varies depending on its view (equatorial, polar), observed layer (exine, intine), focal and angle of rotation. Nevertheless, pollen of different taxa look similar due to the round shape. This is a challenge to the recognition method. Some taxa are not allergenic, but rather originate from honey plants. But the approach can be easily generalized to be applied to any plants dataset.

5 Experiments and Results

5.1 Experiment Design

We performed experiments on three datasets containing five (with most representative shape), nine and 11 number of classes to estimate the impact classes. We augmented poorly presented classes up to 200 images per class by shifting, rotation, flipping. We chose our previous work [14] and work [9] as a baseline since its authors use lighting microscope image dataset with comparable number of classes. For evaluating results, we use accuracy score and cross entropy. We use 5-fold cross-validation. The experiments were conducted on a computer with a Tesla K80 GPU with 128 GB of RAM.

5.2 Prediction Results

We found that on the 5-classes dataset the CNN demonstrates the state-of-the-art results, 99.8% of accuracy, cross entropy is 0.013 (Table 1). As one can see, the accuracy has fallen on the full dataset significantly (95.9% of accuracy, cross entropy 0.17) because the last plant species is very similar to another one, both species belong to one plant genus. In comparison with the baseline ([14, 9]) and in comparison with most of research results in this field related to lighting

[3]`http://genome.ifmo.ru/files/papers_files/ESANN2018/Preprocessed_image_examples.eps`

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Fig. 2: Weights visualization: last layer kernels

microscope, our approach achieved almost the highest result. The preprocessing true positive rate is 92%.

Table 1: Results comparison

# classes	Baseline [14]	Baseline [9]	Proposed approach
5	98.3%	87%	99.8%
9	95.2%	-	97.5%
11	-	-	95.9%

5.3 Deep Feature Visualization

Convolutional neural network extracts features by setting the weights used for convolution. We visualized the weights of the last convolutional layer. The set is 16×32 weights with size of 5×5 (most represented weights are in Figure 2). Kernels look like parts of pollen grains: edges, spots or apertures on the surface of pollen grains.

6 Conclusion

In this work, we address the problem of automated pollen grains recognition. The problem is not novel and has a strong research background. The field of current research is hay fever and asthma preventing through detecting allergenic pollens in the air on images from microscope.

In this paper, we suggested to apply a deep convolutional network that allows to completely avoid both manual feature extraction and the preprocessing step. We built our own configuration that showed state-of-the-art results: 99.8% of accuracy on 5 classes and 95.9% of accuracy on 11 classes pollen images.

We proposed the new approach for preprocessing (pollen extraction) provided by CNN layer outputs, or hypercolumns, with following binarization by clustering and watershed segmentation. This approach shows a true positive rate is of 92%.

These results confirmed the effectiveness of applying CNNs to such specific task as pollen grain image recognition and inspired us to improve it staying under deep learning approach. We plan to apply one-shot learning [18], a transfer learning method that would improve scalability of pollen classes recognition

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unlike CNN without seeing many their examples. Also, in the future we plan to use only deep learning for image segmentation.

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