Pollen detection from honey sediments via Region-Based Convolutional Neural Networks

Philipp Viertel[1], Matthias König[1] and Jan Rexilius[1]

Abstract: This paper deals with the localization and classification of pollen grains in light-microscopic images from pollen samples and honey sediments. A laboratory analysis of the honey sediment offers precise information of the honey composition. By utilizing state of the art deep neural networks, we show the possibility of automatizing the process of pollen counting and identification. For that purpose, we created and labelled our own data set comprising two pollen classes and trained and evaluated a regional-based neural network. Our results show that the majority of pollen grains are correctly detected. The pollen frequency in the honey sediment is on par with the majority pollen class, however, more samples and further investigation are required to ensure stable results and practicality.

Keywords: Deep Learning, palynology, melissopalynology, pollen analysis, object detection

1 Introduction

Computer Vision covers algorithms and methods to extract sensible information from visual data. Significant progress has been made in recent years in robotics, medicine, biology, and other fields of application by utilizing deep neural networks and ever increasing computational power, coining the term Deep Learning (DL). A typical task in this regard is object detection, which usually refers to a combined task of classification and localization of instances of classes in an image and providing the position and number of each appearing class.

Palynology is the scientific study of particulate samples and especially pollen, which is a powdery substance containing pollen grains. Pollen stem from seed plants and contain the haploid male genetic material and play a crucial role in the pollination of the female reproductive structure by wind or insects. Pollen is also a characteristic ingredient of honey. Bees collect nectar from plants and during this process, due to vibrations caused by wind or by touching the stamen, pollen grains are released into the air and mixed with nectar. Therefore, the pollen in honey give important information about its botanical and geographical composition and origin.

Beekeepers are required to know the ingredients of their honey to label their products correctly, otherwise they have to refer to generic names, such as spring honey, which also

[1] Bielefeld University of Applied Sciences, Campus Minden, Artilleriestr. 9, 32427 Minden, [Firstname].[Lastname]@fh-bielefeld.de

lacks adequate allergy information. Therefore, beekeepers depend on professional laboratory analysis of their honey, which is performed by highly trained palynologists, who identify and count the pollen grains with a light-microscope (LM) by their morphological characteristics [Ha18]. In Germany, the entire process is prescribed by the DIN norm 10760.

The classification of pollen grains with Machine Learning (ML) or DL methods is not new, however, the detection of pollen in honey is a novel project. State of the art methods, such as Convolutional Neural Networks (CNN) have been applied in various disciplines and continue to produce efficient results. Region-based Convolutional Neural Networks (R-CNN) are prominent network architectures which are used for object detection.

Data scarcity is still a problem and large open accessible pollen data sets are limited. Therefore, we created our own data provided by local beekeepers and palynologists. We labelled the data and trained a Mask R-CNN model and evaluated it on test data as well as on honey samples. The results are compared to a professional lab analysis. For our own analysis, we tried to follow the requirements presented in the German DIN norm, to make a case for an automated solution for the problem of honey analysis.

2 Related Work

The benefits and needs of an automated solution, especially when compared to the manual method, were shown as early as 1996 [SF96]. Since then, numerous methods have been proposed. The authors of [Ka19] propose a method to count pollen grains on microscopic slides by detecting the pollen by their shape and color (including pre- and post-processing operations to exclude non-pollen objects). A neural network is used to refine the results. The performance is on par with manual counting results with slight aberrations. A classification of the pollen, however, is not provided. [Go16] uses feature extraction and ML methods on the POLEN23E (35 classes with 805 images) data set. With a set of classifiers, an accuracy of 64 % was achieved. By using DL methods, the authors of [SA18] improved the results and achieved an accuracy of 97 % on the same data set. [SHA20] utilized a pre-trained CNN to extract features and a linear discriminant classifier to perform the classification. For training and validation 19,500 images from 46 pollen types (from New Zealand and the Pacific region) were used, which makes it one of the largest data sets available. Using a 10-fold cross-validation, an accuracy of 97.86 % was achieved.

Two popular and state-of-the-art network architectures exist for the task of object detection: YOLO (You Only Look Once) [RF18] and Mask R-CNN [He17] (which is based on the Fast and Faster R-CNN models). The YOLO models stand out in terms of speed, achieving results in real-time, whereas R-CNNs are superior in classification precision.

3 Method

3.1 Honey sediment

Our honey sample was analyzed in a laboratory. The leading pollen is European chestnut, followed by canola types, and roses. Various other pollen classes are combined in the group “Other”. The complete composition is shown in Table 1.

Pollen	**Amount**
European chestnut (*Castanea sativa/Fagaceae*)	76.3%
Other	8.0%
Canola-type (*Brassica-type/Brassicaceae*)	7.0%
Rose family (*Rosaceae*)	3.3%
Linden (*Tilia/Malvaceae*)	3.0%
Raspberry, blackberry (*Rubus-type/Rosaceae*)	2.3%

Tab. 1: Honey sediment composition. The leading (majority) pollen here is *Castanea sativa*, with 76.3 % of the counted pollen (45 % are the minimum to declare the leading pollen).

A series of images from this sediment was captured and used for evaluation. An important issue when observing pollen grains with a LM is focus. Pollen grains are typically very small, ranging from 10µm to 100µm, and it is very difficult to bring every pollen on the same optical level, despite the use of a cover glass or other containment agents. Therefore, constant focusing is mandatory, during a manual analysis as well as during image capturing. The overall quality is also important, to capture crucial visual traits, e.g. ornamentation.

3.2 Training and validation data

The two most prominent pollen classes in our honey sample are *Castanea sativa* and *Brassica napus*. Therefore, we created a data set[2] consisting of these two pollen classes. The images were all captured with a LM and a magnification strength of 400 X. The same way the images from the honey sediment were created and also in accordance with the DIN norm, which prescribes a magnification strength of 320 X to 1,000 X. Our data set consists of 99 images, which we split into 80 % training and 20 % validation data. The 79 training images contain 251 objects; 183 *Castanea sativa* and 68 *Brassica napus*. The 20 validation

[2] The images are provided by Reinhard Jäger as well as Stebler Th., Pollen-Wiki https://pollen.tstebler.ch/MediaWiki/index.php (Accessed: 29.10.2021).

images contain 67 objects; 33 *Castanea sativa* and 34 *Brassica napus.* Each image contains a number of bounding boxes, which are indicated by x/y-coordinates, and the corresponding class label. This information is stored in a separate XML file for each image. As mentioned in the previous section, due to differences in the optical level, the focus of individual pollen grains can vary to a large degree. It is important to carefully choose which pollen to label, i.e. regard as a valid training sample, and which not. Too much blur can remove crucial characteristics, and although it can increase performance for that specific pollen class, it can lead to false classifications and overgeneralization.

3.3 Model training and evaluation

The detection of pollen grains is not time-critical, however, a precise classification is. Therefore, we utilized Mask R-CNN, an iteration of the R-CNN family. The architecture consists of two modules: first, a region proposal network, which makes proposals concerning the region and objects within this region. Second, Faster/Mask R-CNN extracts the features from the region and produces the bounding boxes and the class labels. The feature maps are generated by a pre-trained CNN. The feature maps as well as the proposals are fed into the RoI (Region of Interest) pooling and the classifier. Our network was pre-trained on the MSCOCO data set [Li14] and ResNet-101 [He16] was used as the model backbone. Only the pre-trained output layers were removed and trained from scratch. We trained for 5 epochs and evaluated the model on the validation set and on a selected number of honey sediment images.

4 Results and Conclusion

On the training data, a mean average precision of **88 %** was achieved and on the validation data **70 %**. Since Intersection of Unity (overlapping areas) as well as the masks are not of interest in this use case, we evaluated the individual results instead: 51 *Castanea sativa* grains were counted (of 33 or 41, when considering the extremely blurred grains), and 43 *Brassica napus* (of 34 or 37 with blurred grains). For both classes we have an over counting (+10 and +6). In total, **94** pollen were counted and identified of **67 (78)** visible pollen grains. Mistakes included pollen grains which were counted twice (as both classes) and a large number of *Castanea sativa* were falsely counted from debris, unidentified objects/grains, and an overcounting of closely connected blobs of pollen, as shown exemplarily in Figure 1.

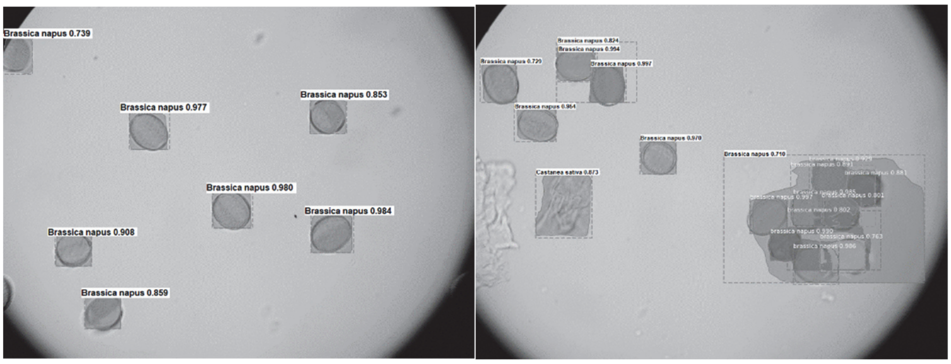

Fig. 1: Two examples from the results. Left: complete correct detection of seven *Brassica napus* pollen grains. Right: case with outliers. A no. of false detections on solely *Brassica napus* pollen, e.g. debris in the center-left (classified as *Castanea sativa*) plus a problematic blob of grains on the right, which was overcounted.

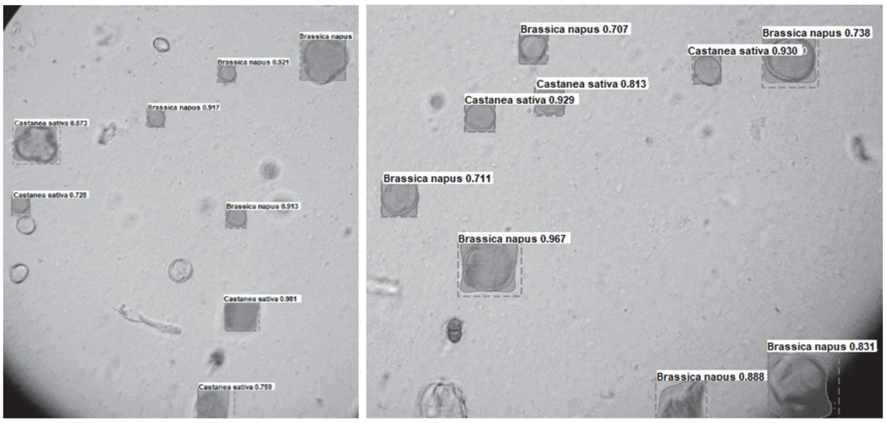

Fig. 2: Two example images from the honey sediment detection. The density of the pollen grains is relatively low and the images contain much more debris, such as dust and other blurry objects. Left: a number of visible pollen grains were not detected. Right: the larger pollen should be *Brassica napus* (size of 22.3-28.2µm, compared to 14.6-17.1µm for *Castanea sativa*).

The DIN norm requires at least 500 pollen grains to be counted, more if there is no stability in the results. Although we did not work with this amount of pollen grains, we evaluated a series of 12 images captured from the honey sediment (as mentioned in Section 3.1). 89 pollen grains were classified, as of which 58 % *Castanea sativa* and 42 % *Brassica napus* (compared to 76.3 % and 7 % in the report, respectively). The images contain more debris and non-trained pollen grains, which make a classification more challenging. This leads to a false over-classification of *Brassica napus*. However, isolating specific pollen clusters and detecting solely in this region can increase the performance. The majority pollen is on par with the results of the manual lab analysis (>45 %), however, more pollen grains would be required to establish the stability of the results and fulfill the norm requirements.

5 Future Work

The quantity of training data needs to be increased and should be more varied, in order to capture a larger variety of perspectives and positions of the pollen grains. This will increase the prediction results, especially in more complicated cases. The sediment creation process can be improved as well. Laboratory centrifuges are more efficient and can produce a higher number of pollen per 20µl sediment (4,000 to 6,000, while non-laboratory methods produce 250 to 600 pollen). It is also recommended to work with clear and focused pollen as much as possible, since even a slight blur can remove delicate visual features and alters the performance in an unpredictable manner. Unfocused or unfavorable single images of pollen grains are not even properly identifiably by palynologists. However, we believe that an automated system for honey analysis is possible and can support the time-consuming and labor-intensive laboratory work, by counting and identifying the leading pollen classes in a honey sample and producing a reliable estimation.

References

[Ha18] Halbritter, H. et al.: Illustrated Pollen Terminology. 2nd ed., Springer International, 2018.

[SF96] Stillman, E. C.; Flenley, J. R.: The needs and prospects for automation in palynology. In: Quaternary Science Reviews, vol. 15, no. 1, pp. 1-5, 1996.

[Ka19] Kadaikar, A. et al.: Automatic Pollen Grains Counter. In: 3rd International Conference on Bio-engineering for Smart Technologies (BioSMART), pp. 1-4, 2019.

[Go16] Gonçalves, A. B. et al.: Feature Extraction and Machine Learning for the Classification of Brazilian Savannah Pollen Grains. In: PLOS ONE, vol. 11, no. 6, 2016.

[SA18] Sevillano, V.; Aznarte, J. L.: Improving classification of pollen grain images of the POLEN23E dataset through three different applications of deep learning convolutional neural networks. In: PLOS ONE, vol. 13, no. 9, 2018.

[SHA20] Sevillano, V.; Holt, K.; Aznarte, J. L.: Precise automatic classification of 46 different pollen types with convolutional neural networks. In: PLOS ONE, vol. 15, no. 6, 2020.

[RF18] Redmon, J; Farhadi, A.: YOLOv3: An Incremental Improvement. In: arXiv:1804.02767 [cs], 2018.

[He17] He, K. et al.: Mask R-CNN. In: International Conference on Computer Vision (ICCV), pp. 2980-2988, 2017.

[He16] He, K. et al.: Deep Residual Learning for Image Recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770-778, 2016.

[Li14] Lin, TY. et al.: Microsoft COCO: Common Objects in Context. In: Computer Vision - ECCV 2014. Lecture Nores in Computer Science, vol 8693. Springer, Cham, 2014.