Pollen Grain Classification Challenge 2020
Challenge Report

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Abstract. This report summarises the *Pollen Grain Classification Challenge 2020*, and the related findings. It serves as an introduction to the technical reports that were submitted to the competition section at the *25th International Conference on Pattern Recognition (ICPR 2020)*, related to the Pollen Grain Classification Challenge. The challenge is meant to develop automatic pollen grain classification systems, by leveraging on the first large scale annotated dataset of microscope pollen grain images.

Keywords: Pollen grain classification · Computer vision · Machine learning

1 Introduction and Motivations

Aerobiology is a branch of biology that studies the dispersal into the atmosphere of microorganisms, such as viruses, bacteria, fungal spores, and pollen grains [17]. Despite being mainly applied for studying the effects of airborne biological agents on human health [28], aerobiology also plays an important role in other fields, such as in plant [32] and environmental sciences [18,26]. In particular, monitoring airborne pollen dispersal is important for allergology [6], criminalistics [1], archaeobotany [25], biodiversity conservation [13] and crop modeling [9]. Despite its importance, the hard work required by the techniques currently used to identify and count the relevant entities in microscopy has hindered the application of aerobiology to those and new sectors. Standard palynological procedures rely on the manual classification of pollen grains by observing morphological traits on microscopy images [22]. Indeed, the identification and classification of pollen grains from different plant species require the intervention of qualified human

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Table 1. Comparison between the proposed dataset and the main datasets used in pollen grain classification.

Dataset	Number of grains	Image type	Resolution
Duller's Pollen Dataset [11]	630	Grayscale	25×25
POLEN23E [16]	805	Color	Minimum 250 pixel per dimension
Ranzato et al. [27]	$3,686$ ($1,429$ images)	Color	1024×1024 (multiple grains per image)
Pollen73S [2]	$2,523$	Color	Average size $\leqslant 512 \times 512$
Pollen13K [4]	$>12,000 + \sim 1,000$ examples of debris (e.g., dust, air bubbles)	Color	84×84

operators in a highly demanding process in terms of time and people training. Therefore, the importance of automation in the aerobiological field is crucial to provide valuable improvements, especially for the task of pollen grains classification. As a consequence, different automatic classification approaches have been investigated over the years [20,30]. Recent advances in Machine Learning methods based on deep neural networks have resulted in impressive performances on a variety of problems, such as facial recognition, motion detection, medical diagnosis, among many others. At present, Machine Learning approaches have been widely adopted in object classification applications, providing highly accurate results on large-scale Multi-class datasets [3]. The rapid progress of automatic methods for pollen grains classification will have great impacts on the development of low-cost tools for aerobiologists. Moreover, Machine Learning techniques require a large amount of data, promoting the definition of large-scale datasets. To this end, we collected a set of images related to pollen grains detected in microscope images from aerobiological samples, defining a large-scale dataset composed of more than $13,000$ pollen grains [4] in 5 different categories. Previous studies on automatic pollen grain detection/classification are trained and evaluated on datasets which include from 65 to about $4,000$ number of grains, and most of them report results obtained on self-collected databases. Three public databases are the Duller's Pollen Dataset [11], the POLEN23E [16] and the Pollen73S [2]. The first contains a total of 630 grayscale images of size 25×25, the second one includes 805 color images of 23 pollen species, with 35 images for each pollen type, and the latter is composed of $2,523$ images from 73 pollen types. In Table 1, the main datasets used in pollen grain classification are reported.

2 Dataset Description

The provided dataset consists of more than 13 thousands per-object images collected from aerobiological samples, classified into five different categories: (1)

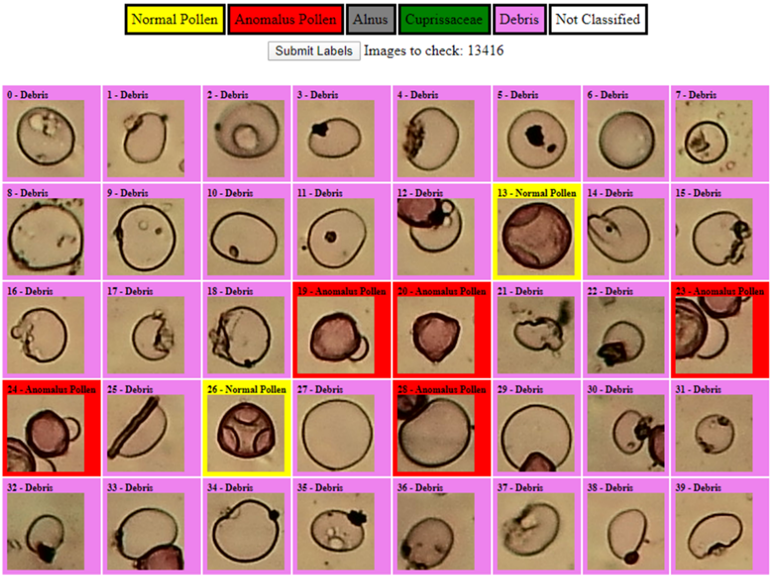

Fig. 1. Web-based tool used to label images

Corylus avellana (well-developed pollen grains), (2) *Corylus avellana* (anomalous pollen grains), (3) *Alnus*, (4) debris and (5) *Cupressaceae*. However, considering the small number of observations related to the class *Cupressaceae*, this has not included in the dataset used for the challenge. Airborne pollen grains were sampled by volumetric spore traps (Lanzoni VPPS®Hirst-type sampler), placed at plant canopy level, with an adhesive strip placed on a rotating drum, moved at 2 mm h-1 under a suction hole, for seven-day sampling autonomy. Thereafter, the sampling strip was collected weekly and cut into daily segments that were analyzed following standard staining procedures. The pollen grains placed on microscope slides were selectively stained with a mounting medium containing basic fuchsin (0.08 % gelatin, 0.44% glycerin, 0.015% liquefied phenol, 0.0015% basic fuchsin in aqueous solution). For image acquisition, the daily strip segments were inspected using a Leitz Diaplan bright-field microscope with a 5 MP CMOS sensor. Then, image patches depicting centered objects automatically extracted from microscope images were manually labeled by experts in aerobiology using a web-based tool (see Fig. 1). The dataset includes:

- 84×84 RGB images for each segmented object, for each of the four categories;
- binary masks for single object segmentation (84×84 resolution);
- segmented versions of the patches obtained by applying the segmentation mask and padding the background with all green pixels (84×84 resolution).

Table 2. Number of objects for each class on training and test set. Training objects represent 85% of the full dataset while test objects the 15%.

Class	Training objects	Test objects
Corylus avellana (well-developed pollen grains)	1, 566	277
Corylus avellana (anomalous pollen grains)	773	136
Alnus (well-developed pollen grains)	8, 216	1, 450
Debris	724	128

3 Challenge

3.1 Description

The aim of the proposed challenge is the automatic classification of pollen grain images exploiting the largest dataset of microscope pollen grain images, collected from aerobiological samples. The microscope images of the samples have been digitalized and processed through a proper image processing pipeline [3] to detect and extract five classes of objects, including four pollen types and an additional class of objects that could be often misclassified as pollen (e.g., air bubbles, dust, etc.). Due to the very low number of examples of the class *Cupressaceae*, this class has been ignored for the classification task proposed by the challenge[1]. More than 13, 000 objects have been detected and labeled by aerobiology experts. The challenge started officially on the 10th of May 2020, when the organizers opened the registration through the website https://iplab.dmi.unict.it/pollenclassificationchallenge. After ten days, when the training data have been released, the challenge counted 96 registered teams. Training data have been available for about one month, and on the 18th of June 2020 also test data have been released, together with an example template file (JSON format) for prediction results upload. The number of objects for each class in the training set and test set is described in Table 2.

3.2 Evaluation Criteria

Participants have been requested to upload the results of classification according to the specified submission format. The submitted classification results have been evaluated considering different metrics. Then, the ranking has been defined considering the F1 weighted score as the first metric, followed by the F1 macro and Accuracy respectively (i.e., F1 (weigh), F1 (macro) and Accuracy in Table 3).

The *F1 weighted score* computes the F1 for each label and returns their average with the number of instances of that class in the dataset. This alters the classic F1 score to account for label imbalance. The *F1 macro score* computes the F1 for each label and returns their average.

[1] More details about the full dataset can be found at: https://iplab.dmi.unict.it/pollengraindataset/dataset.

3.3 Ranking

The submission page was open for five days: 50 teams submitted 87 files in JSON format representing the predicted labels of test data, as requested by the organizers. Four submissions have been removed because in the uploaded file some test instances were missing. Table 3 shows the final leaderboard. Each team was allowed to perform up to five attempts, however, this table shows only the best result for each team. The complete ranking of the accepted submissions listing all the 83 attempts is available at https://iplab.dmi.unict.it/pollenclassificationchallenge/results.

Table 3. Final leaderboard. For each team, only the best result of multiple attempts is reported.

Rank	Username	F1 (weigh)	F1 (macro)	Accuracy
1	zhangbaochang	0.975100	0.955361	0.975389
2	方超	0.973032	0.951970	0.973380
3	Penghui Gui	0.972592	0.951678	0.972877
4	jaideepm.111@gmail.com	0.972578	0.950828	0.972877
5	fangzhouzhao	0.972496	0.951796	0.972877
6	Chia Wei Chen	0.970588	0.950738	0.970868
7	Fangrui Liu	0.969953	0.948511	0.970366
8	Karan Pathak	0.968503	0.945373	0.968859
9	Yutao Hu	0.968093	0.947151	0.968357
10	Yuya Obinata	0.967979	0.946900	0.968357
11	jang_jian	0.967914	0.945436	0.968357
12	Xuihui Liu	0.967001	0.943794	0.967353
13	Vivek Mittal	0.966412	0.941226	0.966850
14	Andrinandrasana David Rasamoelina	0.965974	0.944739	0.966348
15	Nguyen Tu Nam	0.965447	0.940767	0.965846
16	dongdong	0.964497	0.939353	0.964841
17	Alvaro Gomez	0.964423	0.937687	0.964841
18	Alexander Gillert	0.964138	0.938476	0.964841
19	Zhao Qiuyang	0.963047	0.938714	0.963335
20	Amirreza Mahbod	0.962975	0.939495	0.962832
21	Wataru Miyazaki	0.962777	0.935647	0.963335
22	Jonathan Heras	0.961521	0.933872	0.962330
23	Pankaj Mishra	0.961169	0.936951	0.961325
24	Yufei Zhao	0.959996	0.932907	0.960321
25	Narek Maloyan	0.958624	0.928215	0.959316

(*continued*)

Table 3. (*continued*)

Rank	Username	F1 (weigh)	F1 (macro)	Accuracy
26	Gianluca Maguolo	0.957547	0.929319	0.958312
27	Bojan Batalo	0.955266	0.924223	0.955801
28	Bartosz Ptak	0.955024	0.922227	0.955801
29	Melinda Katona	0.954564	0.925895	0.955298
30	Alessandra Lumini	0.952579	0.924816	0.953289
31	Bartosz Ptak	0.951613	0.921605	0.951783
32	Soumyadeep Ghosh	0.951526	0.918610	0.952285
33	Xiaomin Lin	0.948412	0.910667	0.948769
34	Adriano D'Alessandro	0.947723	0.911103	0.947764
35	Soumyadeep Ghosh	0.939999	0.906203	0.940733
36	Umang Chaturvedi	0.939347	0.904577	0.939226
37	Jayasree Saha	0.938737	0.891418	0.941235
38	Umang Chaturvedi	0.931488	0.896115	0.930688
39	Michael Reed	0.916485	0.877608	0.913611
40	Nilesh Kumar	0.916437	0.850337	0.916122
41	Alessandra Crippa	0.911963	0.869167	0.910597
42	Silvio Barra	0.884577	0.841424	0.878955
43	Hussein Osman	0.872832	0.794640	0.874434
44	Abhijith Ragav	0.869042	0.808022	0.860873
45	Austin Lawson	0.797494	0.647156	0.823204
46	Xavier Anadn	0.690048	0.417303	0.735811
47	Oluwatobi Bello	0.518117	0.243847	0.473631
48	Julien Garnier	0.246656	0.321757	0.265193
49	Abhijith Ragav	0.109436	0.086493	0.118031
50	Oluwatoyin Popoola	0.052594	0.093299	0.089904

The leaderboard shows how almost all participants reached good results, with the 0.975 as the maximum F1 value. The average F1 is 0.885 and 82% of the teams outperform this score. Excluding some cases, the proposed methods have achieved slight differences between F1 weighted and F1 macro, which means that the performances of the proposed methods are good for all the classes included in the dataset, although the high imbalance in the data.

3.4 Top 3 Ranked

In this paragraph we summarise the reports for the top-3 ranked Pollen Grain Classification Challenge:

1. **Baochang Zhang et al.:** This is the top-ranking entry by Beihang University (Beijing China) and University at Buffalo (USA). The participants proposed an approach based on two different methods, fused by a proper blending strategy. The first method exploits a neural architecture search with a densely connected search space named DenseNAS [12], which is a neural architecture search method that defines a densely connected search space represented as a dense super network. The super network is composed of densely connected routing blocks that are selected in the search phase to find the best path between them and derive the final architecture. The second method implements a Destruction and Construction Learning architecture [7], which combines a shallow Convolutional Neural Network (CNN) classifier with an Adversarial Network, jointly trained to classify an augmented dataset which includes examples of the training data obtained by shuffling local regions of the original images (i.e., Region Confusion Mechanism). This approach aims at generalizing the classifier on sub-parts of the input image. The blending strategy consists of concatenating the DCL and DenseNAT output vectors to be used as the input of a Random Forest Classifier, which performs the final classification. The authors performed cross-validation tests using the provided train set data, achieving an accuracy of 98,35%. The proposed method obtained an accuracy score of 97,53% when evaluated on the challenge test set. This shows the high generalization capability of such an approach.
2. **Xuhui Liu et al.:** This is the second-ranked entry by Beihang University, Beijing China. Also, this method implements a fusion strategy over two independent pipelines. Specifically, Hierarchical Bilinear Pooling (HBP) [34] and Discriminative Filter Learning within a CNN (DFL-CNN) [31] models are employed. Then, the two outputs are jointly fed to a decision-level fusion model based on a Random Forest Classifier.
3. **Penghui Gui et al.:** Is the third-ranked entry by the College of Computer Science, Sichuan University, China. The solution proposed by this team implements a sophisticated data augmentation approach, which creates a large number of inputs starting from both the provided original and segmented images. In particular, besides common image processing data augmentation procedures, the authors further generated a number of images by applying the cut occlusion approach, which consists of augmenting the dataset with partially occluded versions of existing samples, to encourage the network to consider less prominent features by removing maximally activated features. The trained model is based on ResNet101 [19], followed by additional layers to map high dimensional features of ResNet101 to low dimensional output corresponding to the four classes. It worth mentioning that all three attempts uploaded by this team are ranked in the top-10 global leaderboard[2].

[2] Check the complete leaderboard ranking at https://iplab.dmi.unict.it/pollenclassificationchallenge/results.

4 Relevance of the Results

Since the first applications of neural networks for the classification of pollen grains in light-microscopy [14,24], different machine learning approaches were tested for the scope by different authors (see [20] and [30] for review). Nevertheless, past research has mostly relied on relatively small databases for testing the performances of new classification algorithms [2,11,16,27]. Thanks to the challenge organization, several techniques based on deep neural networks for the classification of pollen grains on the same large scale benchmark database have been evaluated and compared. CNNs were first showed to achieve classification rates higher than 90% for solving pollen classification tasks in [10], where CNN transfer learning was used for both feature extraction and classification. In [30], AlexNet was used for transfer learning and feature extraction, while classification was performed by Linear Discriminative Analysis. This approach achieved an average F-score of 0.967 on the classification of pollen grains contained in the POLEN23E dataset [30]. In another study, the LeNet CNN was applied on a private collection of 1,900 pollen images from four plant taxa, reaching an F-score of 0.928 [23]. Recently, different CNNs were tested for the classification of the Pollen73S dataset, reaching an F-score of 0.964 with DenseNet-201 [2].

During this competition, the contenders had to develop a classifier able to separate instances in challenging conditions, as well-developed hazelnut and alder pollen have similar average dimensions and structures. Moreover, alder pollen was highly over-represented on the images, making correct classification of hazelnut pollen difficult, even for experienced human operators. In this context, the F1-scores obtained by the top competitors were therefore significant and better than what was found in recent studies. Besides, past research never included debris, i.e. bubbles created during the preparation of microscope slides and abiotic particulate matter, as part of the classification problem. This could be relevant especially for aerobiological samples where the abundance of debris can hinder correct pollen identification. CNN-based techniques were recently employed for pollen identification on microscope slides, showing promising results even in the presence of fungal spores, bubbles, debris and dust [15]. Future research should test for possible performance gains of such methods by the inclusion of disturbances in the identification procedure. Aerobiology has historically benefited from the use of simple and relatively low-cost techniques, that have allowed a extensive monitoring of airborne particles around the globe [5]. Its automation, by saving time in sample preparation and manual counting, while increasing the sampling rate, has the potential to open new research opportunities and address unanswered problems (for newly developed aerosol-sensing instrumentation see [8,21,29,33]). Nevertheless, for this to be true, new automated aerobiological tools should hold the cost-effectiveness typical of this discipline.

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