Classification of pollen grains using Convolutional Neural Network

Overview

The classification and study of pollen grains is an important task that has a remarkable contribution to different disciplines including medicine, beekeeping, agronomy, quality control of honey-based products, pharmacy and prevention of allergy and asthma. Their investigation has also been an interesting area of research for scientists, even long before the advent of modern deep learning techniques. Nonetheless, the traditional methods of identification and classification involved manual extraction of discriminant visual features. Which were inefficient and time consuming. Thus, the intervention of deep learning in the domain has significantly benefited the study of aerobiology and palynology and specifically the task of classifying pollen grains. This project proposes a convolutional neural network model to classify four different types of pollen grains from a dataset of about 13,279, 84x84 color images. The work in this literature involves three different techniques. The fist method employs base model developed from scratch. Whereas the second approach makes use of feature extraction techniques from a large pretrained network. In the third method involves fine-tuning a pretrained model. Out of these three different approaches, the best model adjustment is found to produce a training accuracy of 93.47%, validation accuracy of 93.03, more importantly and F1-score of 92%.

Why is it important?

The detection and classification of pollen grains plays an important role in facilitating the study of various domains including medicine, biology, allergenics, agronomy, beekeeping, control of honey-based products and so on[1][2]. Additionally, the prediction of the presence of allergenic pollen grains helps in studying the associated health risks in humans[3]. Pollen grains are known to trigger 90% rhinitis that can cause asthma, if not treated immediately. For example, a research conducted by the American College of Allergy, Asthma, and Immunology, ACAAI indicated that 40% of children and 30% of adults have at least one allergy associated with airborne pollen grains. This is one of the main reasons that the study of the presence of air borne pollen grains and their classification is such an important task. As a result, many classical techniques to carry out the task of classifications, involving manual feature extractions methods, were commonly used until recent times.

But properly classifying pollen grains using hand-crafted feature extraction techniques is not only inefficient and time consuming, but also it merely involved the intervention of experts from that specific area. Moreover, it was prone to errors and time consuming. Yet, to distinctively distinguish the different types of pollen grains, a meticulous investigation of the microscopic images by Palynologists (a person who studies pollen grains and other similar plants and spores) must be conducted. However, applying the traditional techniques apart from being inefficient is notoriously slow compared to modern classification techniques that take advantage of deep learning algorithms.

Generally, the intervention of deep learning methods, and particularly the Convolutional Neural Networks (CNNs) came to rescue from these challenges. These algorithms outperform the traditional methods by a large margin, despite the fact that the computational requirements are high. This is because with the increase of availability of datasets it is difficult to train CNNs with large volumes of data using traditional CPUs. Nonetheless, modern application specific integrated circuits (ASICs) hardware designs such as GPUs are able to handle these large datasets at ease. Indeed, it is more advisable to either use advanced GPUs in local devices or take advantage of the available online resources such as collaborative notebooks, provided by companies such as google and Kaggle. In fact, this project is fully implemented using Kaggle.

Yet it is difficult to implement deep learning algorithms that perform an end-to-end classification of pollen grains without the intervention of experts. Even though a few attempts have been made to fully automate the task of classifying pollen grains, none has succeeded in doing so.

Related Work

As stated above the classification of pollen grains is one of the most interesting areas in aerobiology and palynology. As a result, many researches and classification implementations were carried out on the domain. This section briefly discusses some of the state-of-art literature relevant to the topic.

The research paper referenced in [1], proposed three different CNN implementations of classifying 23 different types of pollen grains from POLEN23E datasets. The methods involved in this are approach are transfer learning, feature extraction and a combination of both. An accuracy of 97% was reported on the classification of unseen images by the model.

Similarly, In [2]the authors used an ensemble based approach for the classification of microscopic pollen grains from ICPR 2020 datasets. The research on this paper employed four different models, namely, EfficientNetB0, EfficientNetB1, EfficientNetB2 and SeResNext-50. They trained the architectures with different image sizes, and their model was found to produce an accuracy of 94.48% and a weighted F1 score of 94.54%. A novel dataset was used for a similar task of classification and detection on the research in[4]. The dataset utilized in this research consisted of 13,310 images of pollen grains which were manually labelled following scientific procedures, by experts on the area. Do this the authors employed two large networks (namely, Alexnet and smaller VGGNET) with and without data augmentation. In the model they employed with the augmentation technique, they added segmentation masks to their dataset. The best performance recorded on this research was an accuracy of 89.63% and F-1 score of 88.97%.

A similarly in [5]. This research as well considered a dataset of 13416, 84x84 microscopic color images of pollen grains of four different types and a fifth of debris. Each of the classes considered on this research paper has a different number of images leading to a ‘class imbalance’, a situation where different objects the classes have different number of images data. The collection of the datasets on this work were obtained after observing the objects via a microscope and discriminating these objects using scientific methods by experts. Some image processing techniques like mean shifted filtering, smoothing using gaussian filters, thresholding and many other techniques were also adopted. It is worth mentioning that the authors of the paper employed classical machine learning and deep learning techniques separately. The results from the traditional machine learning approach indicate highest F1-score of 85% and lowest score of 67%. The second technique of utilized on this research involves deep convolutional neural network (AlexNet) for the classification of same images. Using this algorithm F1-score of 87% is recorded with augmented dataset. When small VGG-16 network is used, it produced an F1-score of 85% for same parameters as used in AlexNet.

Dataset

The dataset used in this project consists about 13,279 images of 84x84 size for four types of pollen grains, out of which the three are known pollen grains while the fourth class is usually misclassified as pollen. The dataset is collected by digitizing microscopic aerobiological samples. The training set consists of 11,279 images and the test set has 1,991 unclassified images. Out of the 11,279 training data 1,566 images belong to the first class, 773 to the second, 8,216 to the third and 724 to the fourth class. Generally, there is a large class imbalance, and third class has the largest number of images.

In the proposed model 20% of the training dataset are split for validation while the remaining dataset is used for training.

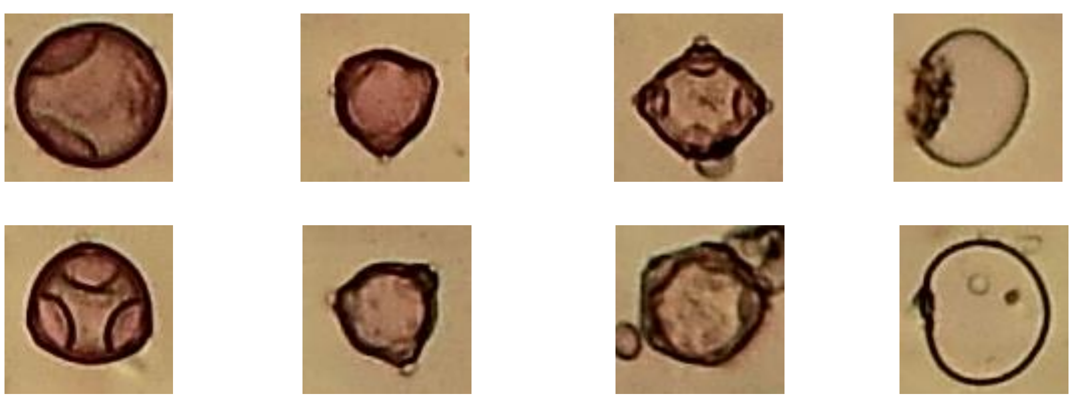

Fig 1: (a) class-1 (b) class-2 (c)class-3 (d) class-4

Experiments and Methodologies

For the task of classifying the image datasets of pollen grains, a base model is developed from scratch. This model is adjusted and fine tunned to produce the best possible results. It employs the basic ideas behind concept of convolutional neural network techniques for developing a classifier. The model consists of four convolution layers all followed by a pooling layer. In the first case the input layers consist of 16, 3x3 kernels and the last layer consist of 128 kernels of the same size. The output of the last layer is then flattened. After a few fine-tuning techniques, a dropout of 0.6 is found to give optimal results. In this approach the available dataset is classified to train and validation sets amounting to 80% and 20% of the images, respectively.

In this method the different available optimizers are experimented, and *Adam* is seen to produce the best results. It is also worth mentioning, that for larger networks (network with large number of parameters), the model highly overfits leading to a network that performs well for the training data but poorly performs on the test data, as shown in figure 1. To fix this we reduced the size of the network and added a dropout layer of 0.6 at the end. This improved the classifier significantly. All the adjustments and experimented results obtained are summarized in table 1. The highlighted row indicates the best results obtained from this method.

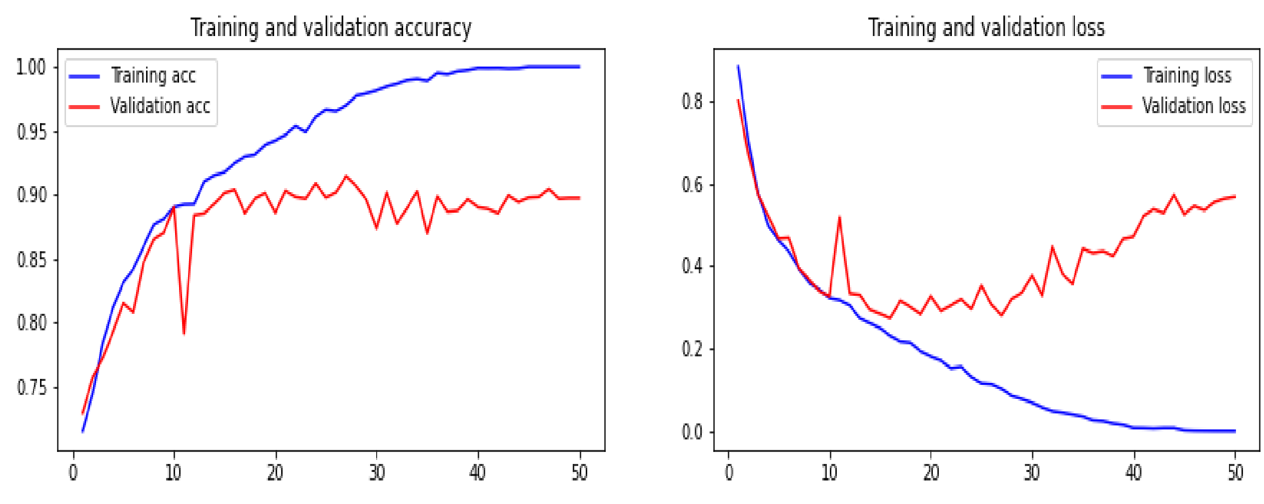

Figure 1: Unoptimized highly overfitting model without dropout

When a dropout of 0.3 is added and the model is trained for 50 epochs, overfitting improved significantly as shown in figure 2. In addition to that, reducing the size of the model and hence the number of parameters also improved the overfitting.

Another important point to note is that model accuracy is not a reliable accuracy matrix because the model may give a higher accuracy that does not represent the actual performance. This is frequently seen in dataset where class images are not balanced. Meaning some classes have larger numbers of images than others. In other words, a model with higher accuracy can still misclassify. To address this issue other metrices such as F1-score, precision and recall are used.

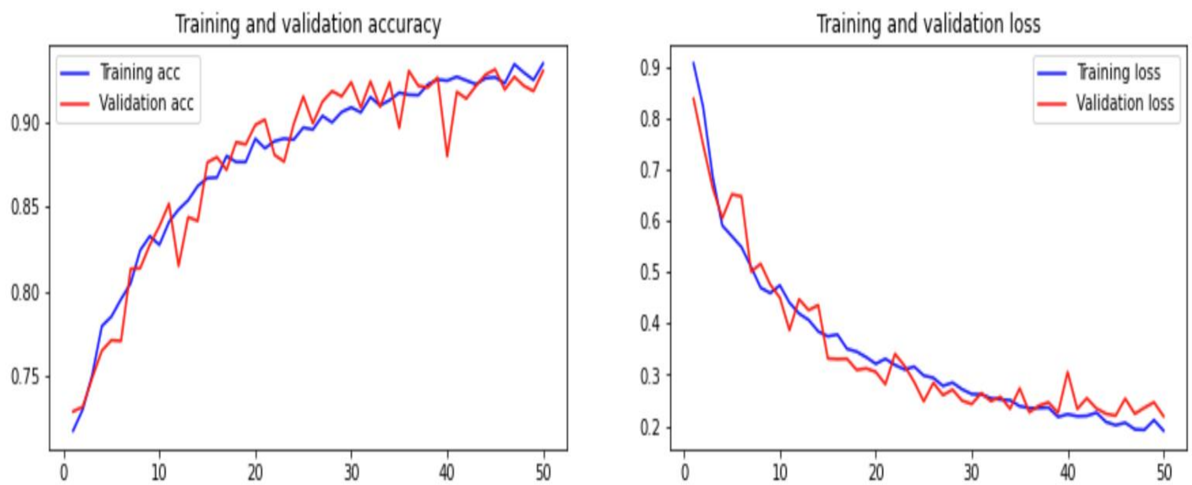

Figure 2: Overfitting improved significantly after adding a dropout of 0.6

S/N	Batch size	No. Epochs	No. params	Train accuracy	Val. accuracy	F1-score	precision	Recall
1	31	35	245,540	94.47	90.02	92.67	94.87	91.23
2	54	35	254,540	95.57	92.77	91.91	93.73	93.27
3	76	35	98,900	96.09	92.81	91.89		92.01
4	**61**	**50**	**98,900**	**93.47**	**93.03**	**92.00**	**93.47**	**92.68**

Table 1. A summary of all the adjustments made to the first method

Results and observations

As it is the usual case, training a model requires some optimization techniques and compromises between the accuracy, and either overfitting or underfitting. But in this project, after adjusting the parameters, promising results of accuracy from a network that does not overfit are obtained. In fact, this is a great achievement compared to the work done previously. As shown in table 1, all the metrics result are very close to each other which was not the case for the work done in other literature.

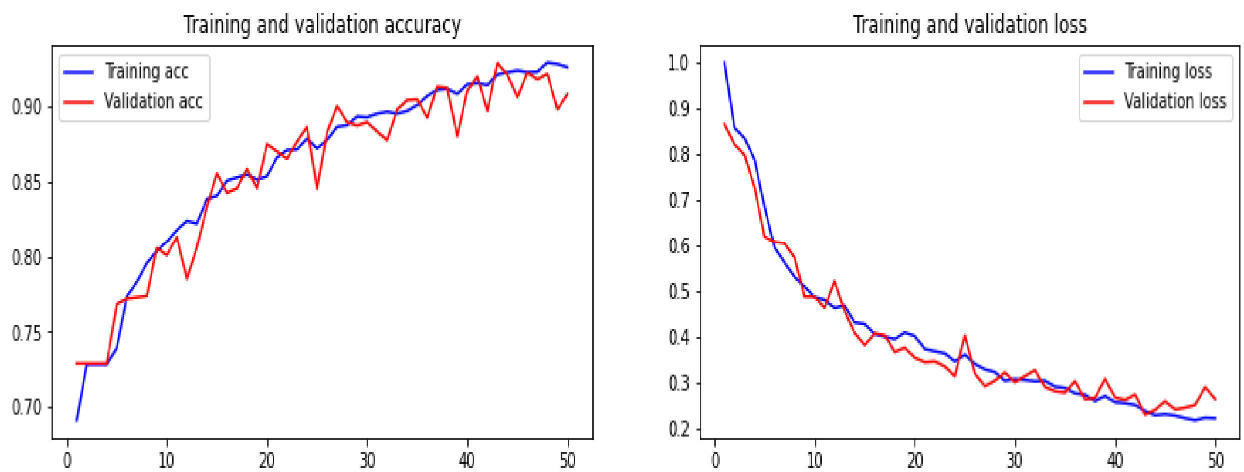

Figure 3: Accuracy and losses for 35 epochs, learning rate of 3e-4 and a Dropout of 0.3

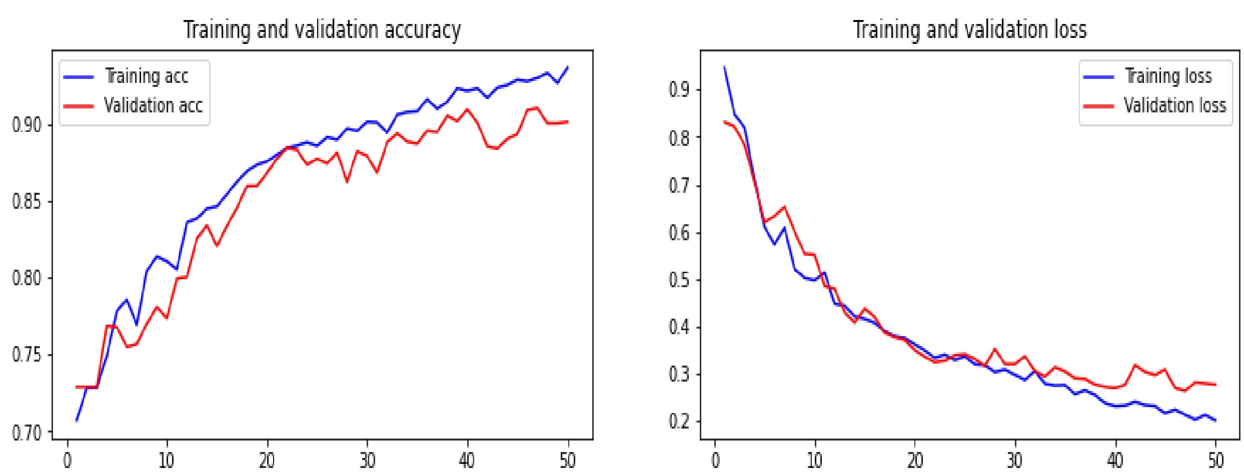

Figure 4: Accuracy and losses for Batch size 760, learning rate = 3e-4, Dropout 0.3 epochs = 50

Future work

As mentioned above, the dataset used in this project is very small and it does not include all the available pollen grains. Therefore, in the future a representative dataset will be collected for better results. Additionally, the number of images for each class in this project are highly unbalanced. For example, the third class has highest number of images up to 8,216, while the fourth class has only 724 images. This difference leads to higher class imbalance. Such a large class imbalance will be reduced in the future work of the project.

Moreover, additional network architectures such as transformer, EfficientNetV1 and EfficientNetV2 will also be investigated and compared.

Reference

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