Deep Convolutional Neural Network for Pollen Grains Classification

Hanane Menad[1], Farah Ben-naoum[1], and Abdelmalek Amine[2]

[1] EEDIS Laboratory, University of Djillali Liabes, Sidi Bel Abbes, Algeria
[2] GeCoDe Laboratory, University of Dr Moulay Tahar, Saida, Algeria

Abstract. The beekeeping is the art of cultivating the bees in the aim to remove from this industry the maximum performance with the minimum expenditure. The apiculture products marketed are the honey, wax, pollen, propolis and royal jelly. This activity of topping up contributes to the development of the livestock and to the protection of the Environment. This paper presents the application of deep convolutional neural network for pollen grains recognition based on their images classification. The neural network contains 8 hidden layers where first 5 are convolutionnal neurones responsible for image representations and next 3 are fully connected layers for image classification. The obtained results proved the efficiency of the proposed approach for pollen grains recognition.

Keywords: Melissopalynology, Honey Pollen Classification, Deep learning, convolutional neural network.

1 Introduction

Honey is a nutritious food, with economic importance for many countries worldwide. Nowadays, increasing attention was dedicated to the determination of the geographical and botanical origin of the honey in the aim to define the differentiation character of honeys of different sources with a standard of quality and authenticity competitive in the market [1].

The melissopalynology or palynology is applied to all knowledge in all relations of any order that exist between the bee and the plant. As such it integrates ecological, ethological and physiological research because it allows the use of pollen grain as a biological marker in the vast context of the relations plant-bee. Pollen analysis of honey is used to differentiate the floral source used by bees, the harvest period and the geo-climatic conditions of the concerned regions [2], palaeoclimatic reconstruction [3], as it has also been used in various medical fields among them allergenic processes [4],etc.

Computationally Motivated Biology is a field that consist of studying biology for modelling the biological systems using the computer science. For this order, researchers study the behavior of a biological system then create tasks as an artificial model to facilitate the task for human beings. It is typically the simulation of a natural phenomenon[5].

Like all machine learning techniques, deep learning aims to cause a system to solve situations without calculating all the necessary parameters to solve them by the implementer. The goal is to train a variable-parameter algorithm (a "black box") to make a correct decision about a given task. Learning is done by optimizing variable parameters to improve the decisions made. Deep learning techniques have made great progress in many areas that range from image recognition [6] .

Founding an efficient automatic classification system for pollen identification becomes a challenge that needs powerful techniques.This paper presents the application of convolutionnal neural network for pollen grains classification. The organisation of the paper was given as follow: Section 2 cites some works on the classification of honey pollen, while section 3 gives an idea about the implementation and results obtained during the experimentations and finally section 4 discusses the major conclusions.

2 Classification of honey pollen

Nowadays, automatic classification for pollen identification becomes a highly active research field. [7] is one of the most recent works, where authors proposed an approach based on features extraction from image and classification of these features using an ensemble classifier based on four different techniques. Another work presented by [8], it was based on multilayer perceptron neural network for classification of pollen species, in which authors claimed that they obtained 100% fo accuracy. [9] also in a work where authors used neural network to classify two sets of microscopic images. In [2], authors used Support Vector Machine to classify melissopalynology data to recognize the origin of the pollen, they identify the marker species that represent the area using z-scores algorithm, and they predicted the area of origin by SVM algorithm, finally they used a statistical analysis of the marker species. The images were collected in Italy, all samples belonged to chestnut honey, so the results obtained showed a high accuracy of discrimination of these samples in Italy. Authors in [10] captured pollen grains from all sides, then they represented them in 3D space to extract Gray- scale vectors from each side, finally they classified these vectors using SVM, the accuracy obtained was about92%. [3] authors extracted texture in order to detect Poles and Furrows for pollen grain recognition then they represented them in 732 variables before they applied MLP NN to choose the important variables. The classification was done using stastical method and leave-one-out for evaluation. To achieve the goal of pollen recognition, authors in [11] proposed an automatic method, based on deep learning framework, the result achieved about 94% classification rate on a dataset of 30 pollen types. Also, in[12] authors present state of the art of deep learning methods applied on POLLEN23E data set, the result show a high efficiency, specialty when they used a hybrid approach,combining transfer learning and feature extraction.

3 The proposed approach and results

The year 2006 was the beginning of the deep learning, then, it has emerged as a new area of machine learning research. Since that, researchers focused on developing deep learning based techniques that impact signal and information processing, especially image processing that get the most part of deep learning development.

Deep Convolutional Activation Feature for Generic Visual Recognition(decaf) is a python framework developped by Donahue et al. in [13], where authors adapted the deep convolutional neural network approach proposed by Krizhevsky et al. in [14] to be implemented on only CPU rather than GPU. The approach is divided into two parts, first part consists of feature extraction from images using ReLU non-linearities convolutional computation, then dimentionality reduction using pooling technic, this part gives as result a vector of 2048 elements to represent each image. The second part, is a 3 fully connected layers for image classification.

3.1 Pollen23E dataset

Pollen23E is a set of 805 images divided in 23 species (classes). Each class comprises of 35 images captured by a digital Bresser LCD microscope at a 40x magnification from different angles. Then the obtained images were transfered to a laptop and segmented using the CorelDRAW1 software. [15].

3.2 Obtained results

In the following, we discuss the obtained results, in which, we based on the best training accuracy, best validation accuracy, best cross entropy and test accuracy to evaluate the effect of number of iterations on pollen grains classification:

Table 1. Obtained Resutls

Number of iteration	Training Accuracy	Cross Entropy	Validation Accuracy	Test Accuracy
100	99	1	96	76.6
200	100	0.53	95	85.1
500	100	0.38	98	85.1
1000	100	0.12	99	83
1500	100	0.07	100	85.1
2000	100	0.05	99	85.1
2500	100	0.04	100	85.1
4000	100	0.02	100	85.1

As seen in table 1, number of iteration affected the obtained results in a manner that if we add more iterations, neural network builds better models. And this is clear in terms of first three measures:

– *in terms of Training accuracy:* This measure is the accuracy of applying the model on the training data, it is used to evaluate the model during backpropagation steps in order to improve the model. In table 1, we cited the best training accuracy obtained, as seen, the model is perfect since it correctly classified 99% to 100% of training data. Figure 1 shows a detailed updates of training accuracy during each iteration where (a), (b), (c), (d), (e), (f), (g) and (h) present 100, 200, 500, 1000, 1500, 2000, 2500 and 4000 iterations respectively.

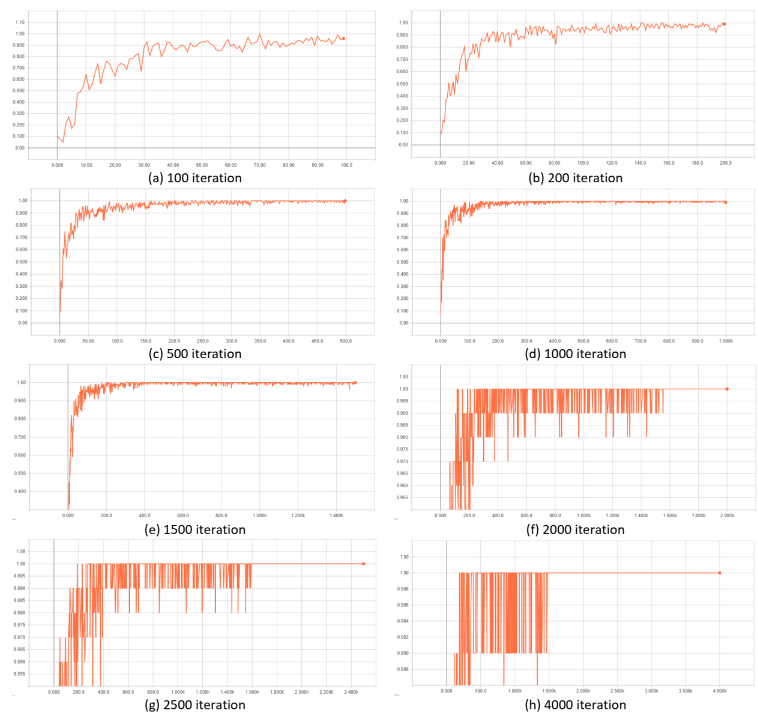

Fig. 1. Training Accuracy updates during each step

For all cases, we see in figure 1 how the training accuracy begins with small values (about 5%), then it improved iteration after iteration to reach 100%.

– *in terms of Cross Entropy:* When we use cross entropy loss while training neural networks, we actually calculate the score function every time when compute gradients for the weights in the network. So, the objective is minimizing this measure, as seen in table 1, when we added more iteration, the neural network minimized the cross entropy which means we got better models. Figure 2 shows a detailed updates of cross entropy during each iteration where (a), (b), (c), (d), (e), (f), (g) and (h) present 100, 200, 500, 1000, 1500, 2000, 2500 and 4000 iterations respectively.

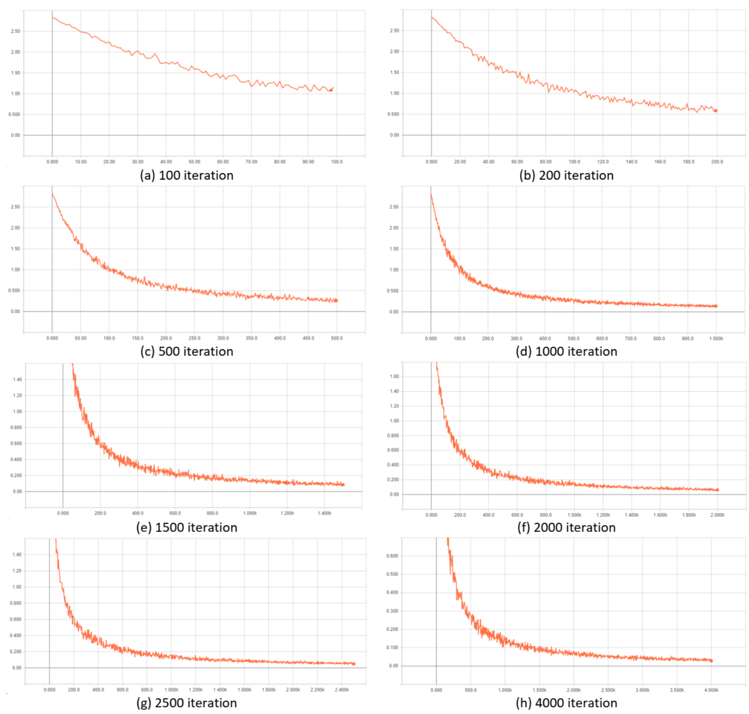

Fig. 2. Cross Entropy updates during each step

For all cases, we see in figure 2 how the entropy begins with high values (about 5), then it improved iteration after iteration to converged to 0. While detailing the figures, we see that more we added iterations, the cross entropy became lower which means we have reduced information loss by improving the model.

– *in terms of Validation accuracy:* This measure is the accuracy of applying the model on the validation data, as training accuracy, it is also used to evaluate the model during backpropagation steps in order to improve the model. In table 1, we cited the best validation accuracy obtained, as seen, the model is perfect since it correctly classified 95% to 100% of training data. Figure 3 shows a detailed updates of validation accuracy during each iteration where (a), (b), (c), (d), (e), (f), (g) and (h) present 100, 200, 500, 1000, 1500, 2000, 2500 and 4000 iterations respectively.

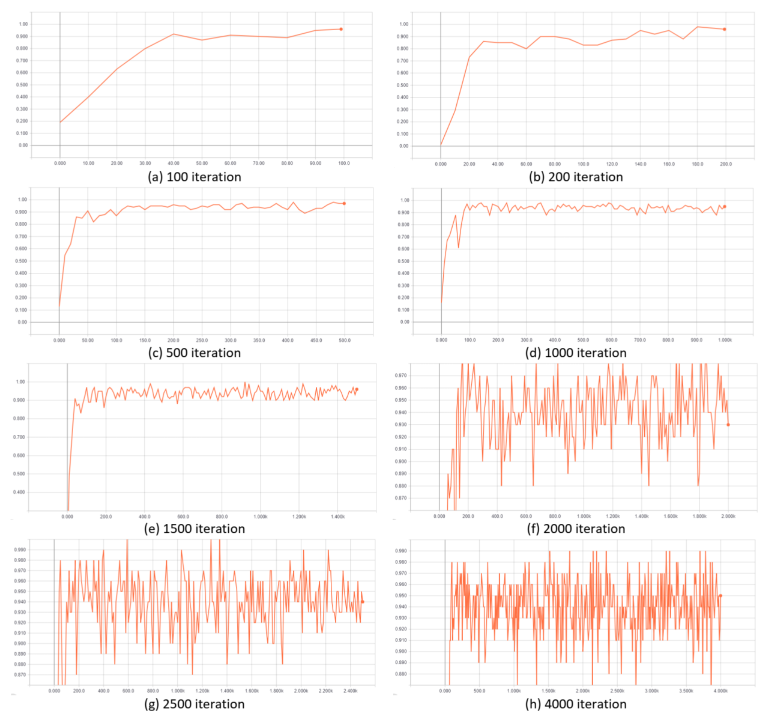

Fig. 3. Validation Accuracy updates during each step

For all cases, we see in figure 3 how the validation accuracy begins with small values (about 5%), then it improved iteration after iteration to reach 100%. Also, since validation accuracy is lower than training accuracy, we validated that our model did not suffer from under fitting problem.

– *in terms of Test accuracy:* This measure is the accuracy of applying the final model on the test data, it is used to evaluate the prediction of new images. Figure 4 shows the comparison of test accuracy according to number of iteration.

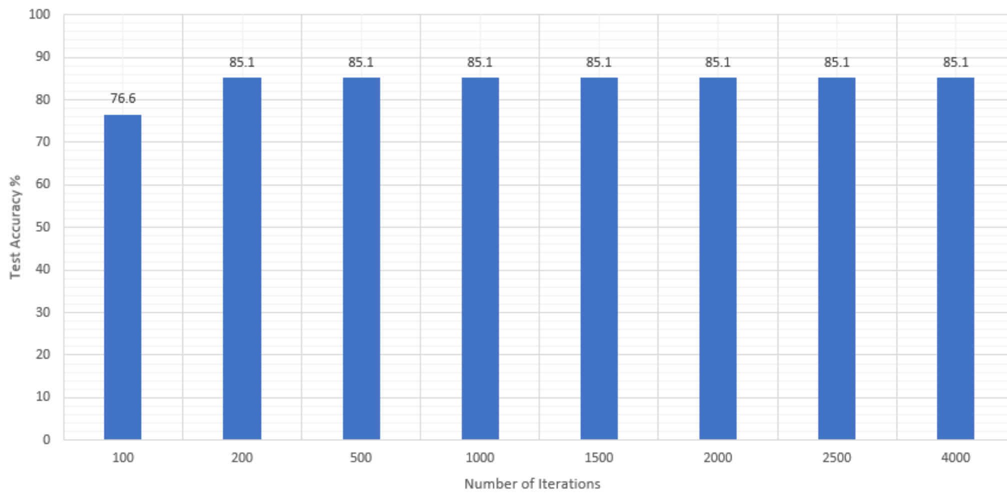

Fig. 4. Test Accuracy according to iteration numbers

In our case (figure 4, the model recognized 76.6% of test images when we built a model in 100 iterations, while it was improved when we augmented the number of iterations to 200 iterations to recognize 85.1% of pollen grains, then it became fixed despite the model has been improved based on previous measures.

3.3 Comparative study

To validate better our study, we compared our obtained results with other results from literature. [12] is a work that applied deep learning for pollen classification using the same Pollen23E dataset. Cho et al. implemented three different setups, the first setup (TL) consist of using deep learning neural network for feature extraction and classification of images, the second setup setup (FE+LD) consists of using deep learning neural network for feature extraction and descriminant learning for classification, while the third setup (TL+FE+LD) is a hybridization of both setups where in classificatio phase, they used both neural network and descriminant learning for pollen recognition. Figure 5 shows the comparison done:

As seen, after reimplementing approaches proposed by [12] to compare them in the same conditions as our proposed approach, our obtained results were in general better than results gotten in [12]. The problem in Cho et al. work was

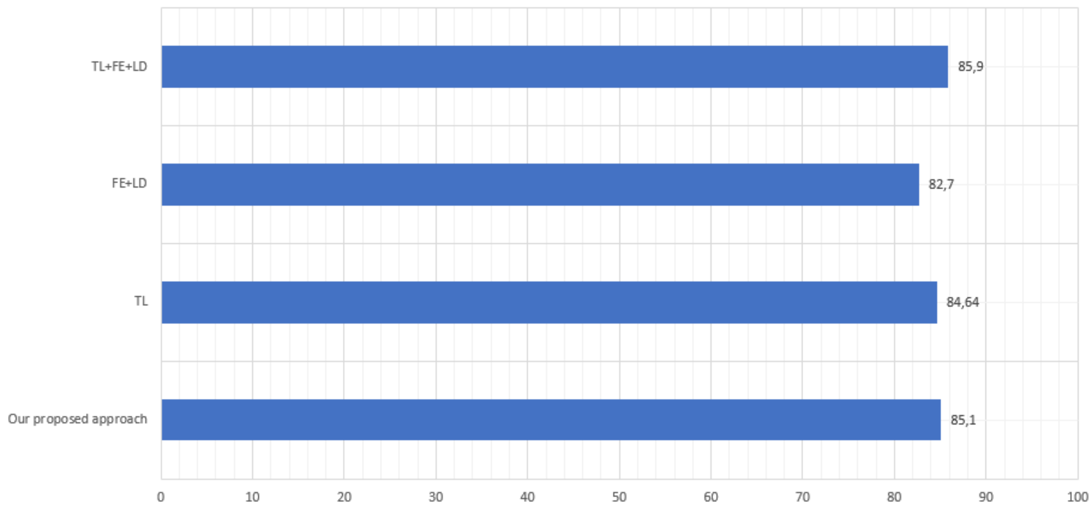

Fig. 5. Comparison between our obtained results and the ones obtained in [12]

the information loss, since they applied many filters for either feature extraction or classification which cause a lot of information lost during these processes. Contrary to our work, where we used only pooling technic for dimentionality reduction, consequently, we minimized the information loss.

Another comparison was done with same work, since they used deep neural networks as our objective, so we compared the time complexity taken by each approach with same conditions (number of iteration), Figure 6 shows the comparison:

As seen in figure 6, we reduced the training time, and the difference of time reduced became higher when we increased the number of iteration for each approach, in which we gained from 0.47 minute up to 1.38, when we used 100 iteration, while the use of 4000 iteration proved that we can gain between 1.23 up to 2.17 minutes, and these values were obtained when we trained neural networks using 790 images, so we believe that our proposed approach will be more effective in big data image analysis in terms of training time.

4 Conclusion

In this work, we applied a deep convolutional neural network for pollen identification from their images. The approach was divided into two processes, the first process was feature extraction using ReLU non linearities convolutional calculation, where 5 layers were responsible for it, then, the dimentionality of those obtained features were reduced using pooling method to get vectors of size of 2048 element i which each vector represent an image in the dataset. After getting the vectors, they were used a s input to 3 fully connected layers for classifica-

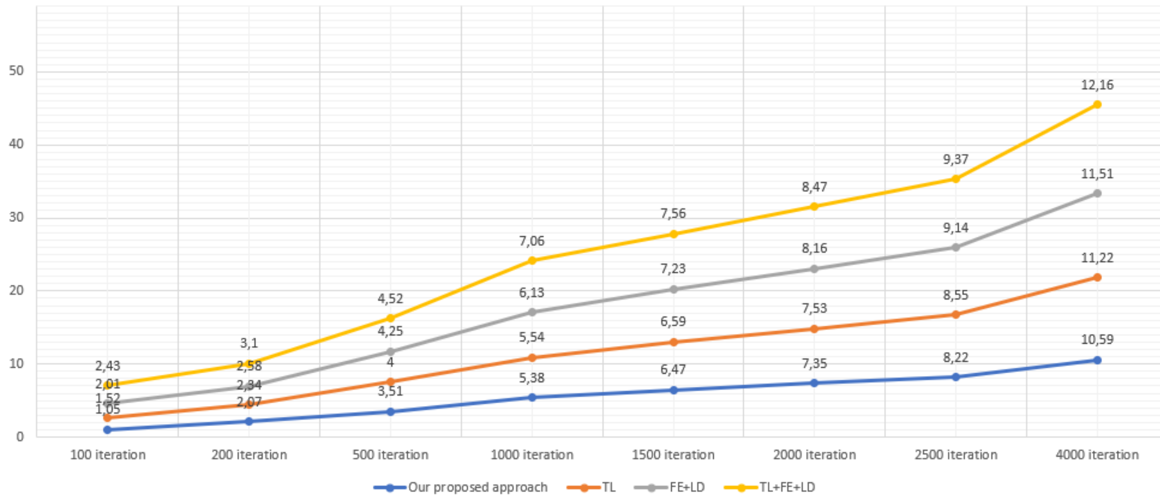

Fig. 6. Comparison between our obtained results and the ones obtained in [12] in terms of training time

tion. The evaluation was based on four measures: Training accuracy, validation accuracy, cross entropy and test accuracy. As seen in the paper, the obtained measures' values proved that deep convolutional neural networks can be used as a good solution to automate the pollen grains classification. Also, we saw that the proposed approach avoid the underfitting, this is proved by the validation accuracy that was lower than training accuracy.

These results motivated us for future works, we planned to develop more deep learning approaches, and combine it with metaheuristics.

References

1. Alissandrakis, E., Daferera, D., Tarantilis, P. A., Polissiou, M., & Harizanis, P. C. (2003). Ultrasound-assisted extraction of volatile compounds from citrus flowers and citrus honey. Food chemistry, 82(4), 575-582.
2. Aronne, G., De Micco, V., & Guarracino, M. R. (2012). Application of Support Vector Machines to Melissopalynological Data for Honey Classification. In New Technologies for Constructing Complex Agricultural and Environmental Systems (pp. 144-153). IGI Global.
3. Li, P., & Flenley, J. R. (1999). Pollen texture identification using neural networks. Grana, 38(1), 59-64.
4. Corbi, A. L., Cortes, C., Bousquet, J., Basomba, A., Cistero, A., Garcia-Selles, J., ... & Carreira, J. (1985). Allergenic cross-reactivity among pollens of Urticaceae. International Archives of Allergy and Immunology, 77(4), 377-383.
5. Devillers, J., Morlot, M., Pham-Delegue, M. H., & Dore, J. C. (2004). Classification of monofloral honeys based on their quality control data. Food Chemistry, 86(2), 305-312.

6. Cho, K., Van Merrinboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning phrase representations using RNN encoder-decoder for statistical machine translation. arXiv preprint arXiv:1406.1078.
7. Arias, D. G., Cirne, M. V. M., Chire, J. E., & Pedrini, H. (2017, December). Classification of Pollen Grain Images Based on an Ensemble of Classifiers. In Machine Learning and Applications (ICMLA), 2017 16th IEEE International Conference on (pp. 234-240). IEEE.
8. Li, P., Treloar, W. J., Flenley, J. R., & Empson, L. (2004). Towards automation of palynology 2: the use of texture measures and neural network analysis for automated identification of optical images of pollen grains. Journal of Quaternary Science: Published for the Quaternary Research Association, 19(8), 755-762.
9. France, I., Duller, A. W. G., Duller, G. A. T., & Lamb, H. F. (2000). A new approach to automated pollen analysis. Quaternary Science Reviews, 19(6), 537-546.
10. Ronneberger, O., Burkhardt, H., & Schultz, E. (2002). General-purpose object recognition in 3D volume data sets using gray-scale invariants-classification of airborne pollen-grains recorded with a confocal laser scanning microscope. In Pattern Recognition, 2002. Proceedings. 16th International Conference on (Vol. 2, pp. 290-295). IEEE.
11. Daood, A., Ribeiro, E., & Bush, M. (2016, December). Pollen Grain Recognition Using Deep Learning. In International Symposium on Visual Computing (pp. 321-330). Springer, Cham.
12. Sevillano, V., & Aznarte, J. L. (2018). Improving classification of pollen grain images of the POLEN23E dataset through three different applications of deep learning convolutional neural networks. PloS one, 13(9), e0201807.
13. Donahue, J., Jia, Y., Vinyals, O., Hoffman, J., Zhang, N., Tzeng, E., and Darrell, T. (2014, January). Decaf: A deep convolutional activation feature for generic visual recognition. In International conference on machine learning (pp. 647-655).
14. Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems (pp. 1097-1105).
15. Gonalves, A. B., Souza, J. S., da Silva, G. G., Cereda, M. P., Pott, A., Naka, M. H., and Pistori, H. (2016). Feature Extraction and Machine Learning for the Classification of Brazilian Savannah Pollen Grains. PloS one, 11(6), e0157044.