

# Pollen Recognition Using Multi-Layer Feature Decomposition

**Amar Daood, Eraldo Ribeiro, and Mark Bush**

Florida Institute of Technology, Melbourne, Florida, U.S.A.

## Abstract

We propose a method for recognizing pollen types from images. Unlike other methods that measure visual characteristics directly on the pollen image, our method decomposes the images into layers prior to performing feature extraction. The method measures texture and geometrical characteristics in each layer. We tested our method on 1,060 samples of 30 species of pollen. The same dataset is also used to compare the results of other pollen-classification techniques. The findings show the proposed method's classification rate is higher than those produced by classical techniques, and the layering technique increases the classification rate over the direct use of the same features.

## 1 Introduction

Pollen identification is key to paleo-ecology research, forensic sciences, allergy control, and even oil exploration (Holt and Bennett 2014; Hodgson et al. 2005). Forensic scientists can solve criminal cases by geolocating the source of pollen samples found in crime scenes (Rodriguez-Damian et al. 2006). Allergy-control scientists determine the allergen levels of spores and pollen collected from aerial traps (Boucher et al. 2002). Paleo-ecology scientists use fossil pollen to map Earth's climate for thousands of years in the past (McMichael et al. 2013).

Despite of its many applications, pollen identification is still mostly done by visual inspection. For example, pollen counting in an allergen-monitoring facility may occupy technicians for some 16 hours a week (Dell'Anna et al. 2010), as they identify pollen types by morphological characteristics such as shape, symmetry, and ornamentation of the grain (del Pozo-Banos et al. 2015; Rodriguez-Damian et al. 2006). In addition to morphological characteristics, surface texture is also used for pollen identification. However, examining these visual attributes requires expert training, and results are subjective (France et al. 2000).

The availability of an automated pollen-identification system would reduce data-collection times in the above fields from months to a few hours, and also increase the quality of the data (Flenley 1968). Since Flenley (1968) suggested the

use of algorithms for counting pollen in palynology, a number of methods have been proposed. Early methods focused on measuring visual characteristics of pollen grains such as shape. The grain's contour shape is a distinguishing feature for certain pollen types that have rounded triangular shapes, elongated elliptical shapes, and circular shapes (Treloar, Taylor, and Flenley 2004; Travieso et al. 2011; Garcia et al. 2012). Surface texture is also a popular feature used by pollen-classification methods (M.Fernandez-Delgado et al. 2003; Li et al. 2004; Guru, Siddesha, and Manjunath 2013; Da Silva et al. 2014). These methods classify pollen types that are distinguishable solely by these cues. Additionally, the combination of multiple visual cues was adopted in some previous works (Allen et al. 2008; Ticay-Rivas et al. 2011; Chica 2012; Lagerstrom et al. 2013).

We propose a method for classifying pollen grains detected in images. Our method combines visual cues of texture, shape, and morphological features (e.g., pours, curves) to form a multi-layer description of the pollen grain. The method starts by decomposing the pollen grain into multiple layers of segmented regions using a clustering algorithm. Each layer contains information about regions with similar gray-level intensity. We then characterize each segmentation layer using a fractal descriptor (to measure shape information), local binary pattern histogram, and statistical measures (to account for texture information). We tested our method on a dataset of 30 pollen types, containing some 1,000 pollen samples provided by the Florida Tech's Paleoecology Laboratory. Figure 1 shows the pollen samples that were used to test our method. Our method produced a classification rate of 87%, which compares favorably to other pollen-identification techniques.

## 2 Related works

Many pollen-classification methods have been published in the past two decades. These methods extract features that describe pollen information such as geometry, morphology, and texture. Using roundness, perimeter, and area features, Treloar, Taylor, and Flenley (2004) proposed a method that used Fisher linear discriminant for classifying 12 types of pollen imaged using scanning electron microscopy (SEM). Geometrical characteristics were also used by Kaya et al. (2014) to train an artificial neural network for classifying ten species from the *Onopordum* pollen family. Character-

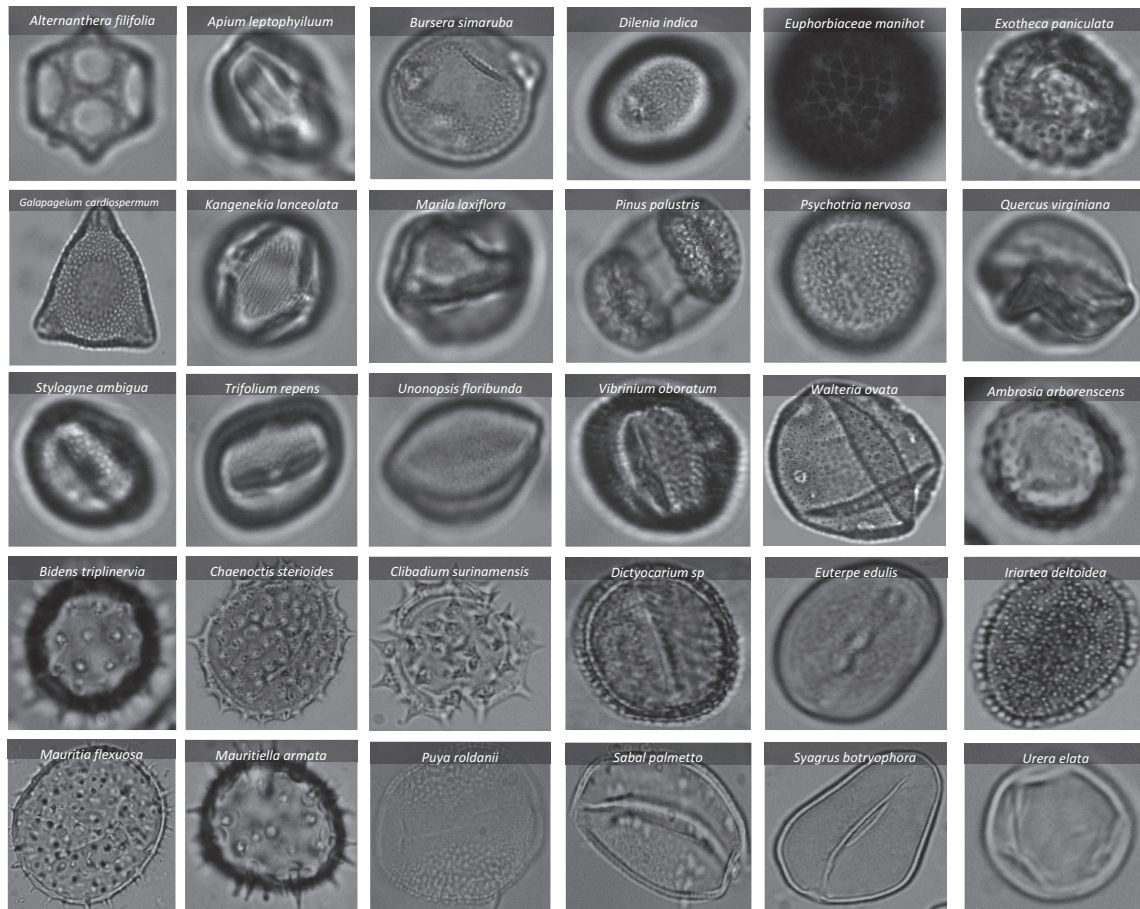


Figure 1: One sample from each pollen type of our dataset. The dataset consists of 1,000 images of 30 pollen types, provided by the Florida Tech's Paleoecology Laboratory.

ists used by Kaya et al. included the colpus length, the colpus width, the equatorial axis, and the polar axis. Travieso et al. (2011) used the pollen grain's contour shape to classify 17 pollen types using light microscopy images. The contour was extracted using an edge-detection algorithm. Then, edge coding was applied to create contour descriptors. Finally, classification was performed by combining a Hidden Markov Model (HMM) and a support-vector machine classifier. However, geometrical and morphological features cannot discriminate pollen species that have similar shapes.

When classifying pollen of similar contours, surface texture is a common choice of feature. Texture characterization based on Gabor features and moment invariants were used by Zhang et al. (2004). They trained a neural network to discriminate five types of pollen grains. The spatial co-occurrence of textons (i.e., learned texture components) was used by Dahme, Ribeiro, and Bush (2006) to classify ten types of pollens grains. Here, textons were obtained by clustering the response of a bank of filters of various orientations and scales. The classification of 18 pollen species from SEM images was presented by Guru, Siddesha, and Manjunath (2013), based on surface texture using a nearest-neighbor

classifier with five different features: wavelet, Gabor, local binary pattern (LBP), gray-level difference matrix (GLDM), and gray-level co-occurrence matrix (GLCM).

When used in isolation, characteristics such as texture and contour may be insufficient for discriminating some pollen species. Hence, the combination of multiple features was used in some methods. Allen et al. (2008) identified six pollen types using 43 characteristics that included shape and texture features such as histogram statistics, moments, a gray-level co-occurrence matrix, and Gabor filter responses. Combined shape and texture features were also used by Nguyen, Donalson-Matasci, and Shin (2013) to classify nine pollen types. Extracted shape features were area, diameter, perimeter, compactness, roundness, thickness, elongation, centroid, eccentricity, and circularity. Texture features were extracted based on the gray level co-occurrence matrix (GLCM) and the gray-level run length. In addition, spike count was computed. Finally, a boosting technique was used for classification. Marcos et al. (2015) combined shape and texture features based on a gray-level co-occurrence matrix, Gabor features, local binary patterns, and moments to classify 15 pollen types using K-NN classifier.

### 3 Our method

We propose a method for pollen recognition based on light microscopy images. Our approach adopts a multi-layering technique. It decomposes the pollen image into multiple layers of segmented regions prior to feature extraction.

#### 3.1 Feature extraction

First, we normalize the image pixel using histogram equalization (Gonzalez, and Woods 2006). Then, we decompose the pollen image into multiple layers using clustering where each cluster represents a layer of pollen grain regions. To improve the consistency of regions in each layer for similar pollen types, we modified the K-means algorithm to sort the resulting clusters based on gray-level intensity. After clustering, the image of pollen is represented as:

$$R = \{L_1, L_2, \dots, L_d\}, \quad (1)$$

where  $d$  is the number of layers and  $L$  represents an individual layer of a pollen grain sample which is given by:

$$L_i = \{c_i, V_i\}. \quad (2)$$

Here,  $c_i$  is the cluster center of the  $i$ -th layer, and  $V_i$  are the pixels inside cluster  $i$ . Then, we reorder the representation ( $R$ ) according to the intensity of the clusters. The sorting process helps keep the order of the layers consistent, from the darker to lighter clusters.

Feature extraction process is performed on each layer. Extracting features for each layer individually improves the representation of the visual information. We adopt different types of features. The local binary pattern histogram suggested by Ojala, Pietikainen, and Maenpaa (2000) and fractal dimension are used to describe each layer. In addition, gray level and histogram statistics are extracted and combined to create feature vectors. The Hausdorff algorithm is adopted to calculate the fractal dimension of decomposed images (Costa, Humpire-Mamani, and Traina 2012). Figure 2 shows the block diagram of the method.

#### 3.2 Classification

Classification is done using support vector machine (SVM) (Cortes and Vapnik 1995), a given a training data  $D$  consisting of  $n$  samples of the form:

$$D = \{(x_i, y_i) | x_i \in R^p, y_i \in \{1, -1\}\}, \quad (3)$$

where  $x$  is training samples,  $y$  is the class label of the training data, and  $p$  is the dimension of the samples. SVM determines a hyperplane in high-dimensional space that classifies the input data into two categories. This hyperplane is:

$$F(x_i) = w^T x_i + b, \quad (4)$$

where  $w$  and  $b$  are the hyperplane parameters, which are determined by finding the nearest samples to that hyperplane. These samples are the *support vectors* and the distance between them is the *margin distance*. The solution is an optimization problem that finds the hyperplane that maximizes the margin between the two classes (Hastie et al. 2009).

SVM is applicable for binary classification only. To classify 30 classes of pollen, we adopted the technique called

error-correcting output code (ECOC), which extends SVM to a multiple-class problem (Dietterich and Bakiri 1995). The ECOC implements a multi-class classifier based on multiple binary classifiers. The ECOC approach can be divided into two stages: coding and decoding. In the coding stage, we used a one-versus-all technique to build the code-word for each class. The number of binary classifiers that should be trained with  $K$  class is given by:

$$N = K(K - 1)/2. \quad (5)$$

In the decoding stage, we adopt a loss-based function to predict the class label by minimizing the sum of the binary losses of the trained binary classifiers (Escalera, Pujol, and Radeva 2009), i.e.:

$$\hat{k} = \underset{k}{\operatorname{argmin}} \sum_{j=1}^N |m_{kj}| g(m_{kj}, s_j), \quad (6)$$

where  $\hat{k}$  is the predicated label,  $m_{kj}$  is the element of the coding matrix,  $s_j$  is the score of the trained binary classifier, and  $g$  is the binary loss function. After we extract the features according to our method for each image in our dataset, we train SVM to perform the classification. We divide our data set into 75% as the training set and 25% as the testing set.

### 4 Performance evaluation and results

We compared our method with a number of approaches. These approaches were tested on our dataset. We used the following features:

1. Histogram features (mean and variance of histogram)
2. Gray level statistics (mean, variance, and entropy)
3. Geometrical features (area, perimeter, compactness, roundness, and aspect ratio)
4. Fractal dimension
5. Gray level co-occurrence matrix (GLCM)
6. Moments invariants
7. Gabor features
8. Histograms of oriented gradient (HOG) descriptors
9. Local binary pattern histogram (LBP)

We also compared our method with two works in the literature that combined multiple features: Marcos' method (Marcos et al. 2015) and Silva's work (Da Silva et al. 2014). Marcos et al. (2015) combined the gray-level co-occurrence matrix, Gabor features, local binary patterns, and discrete moments features. Da Silva et al. (2014) decomposed the pollen grain into four layers using a wavelet transform and then the gray-level co-occurrence matrix was computed to create features vector using statistical measurements. Table 1 shows the classification rate results for different experiments using a support vector machine classifier.

We repeated the classification without the decomposition technique by combining a histogram, gray level statistics, fractal dimension, and LBP features. The improved classification rates obtained by our method are shown in Table

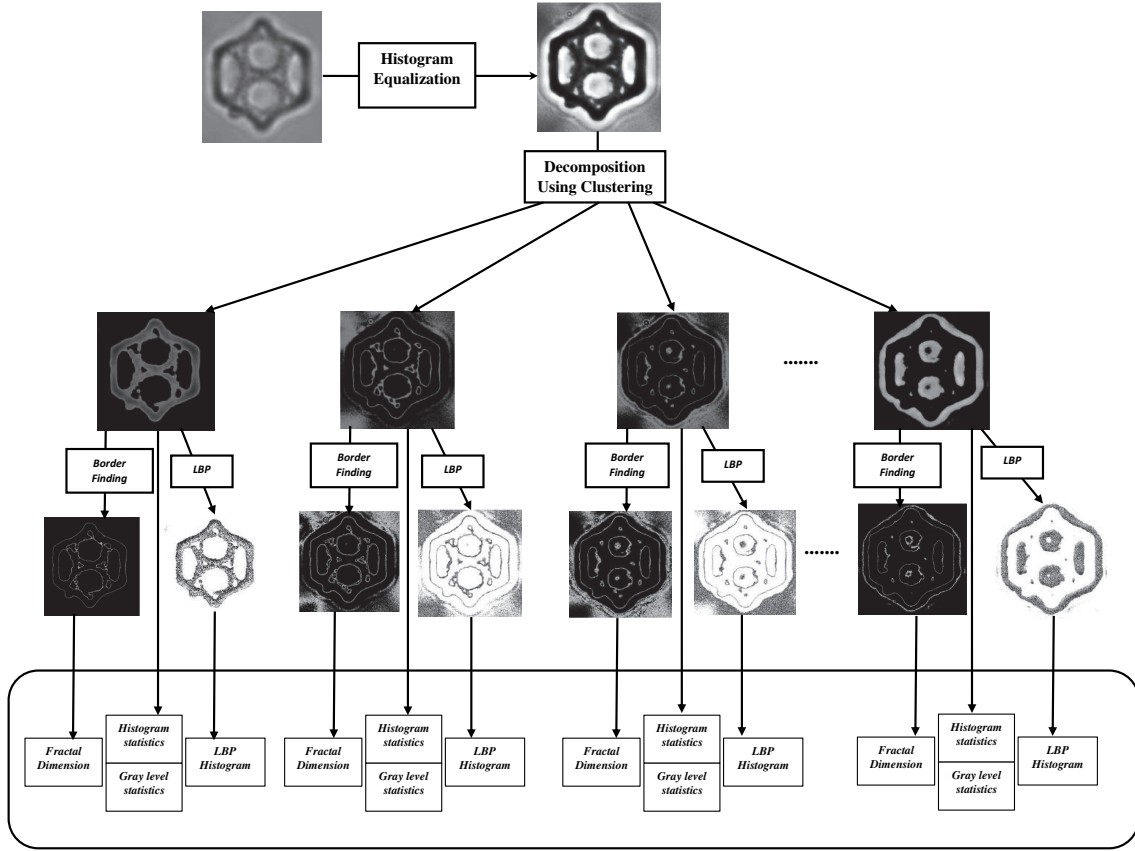


Figure 2: Feature-extraction method in the second stage. First, images are normalized using histogram equalization. Then, the k-means clustering algorithm decomposes the pollen grain into layers containing regions of similar gray-level intensity. Finally, a feature vector is extracted from each layer.

1. Classification using the layering technique gained almost 7% percentage points.

To show the significance of our results, we computed the p-value. Here, we compared the multi-layer decomposition technique with the method that combined a histogram, gray level statistics, fractal dimension, and LBP as features. This combination method obtained a 80.19% classification rate. The p-value was about 0.001, which rejected the null hypothesis. Table 2 shows classification metrics of average of precision, recall, sensitivity, specificity, and F score (Sokolova, Japkowicz, and Szpakowicz 2006). Figure 3 shows the recognition rate of each species for both the proposed method and one using feature combination.

## 5 Conclusion and future work

We proposed a computational method to identify 30 types of pollen grains. The method decomposes pollen images into multiple layers of regions. Each layer is then represented by a set of geometrical and gray-level statistics characteristics. Experimental results showed that our method outperforms the traditional techniques that extract features directly without layered decomposition. While layer decomposition in-

Table 1: Classification rates using SVM

| Method                                       | Classification Rate |
|--|---------------------|
| Histogram features, gray level statistics    | 70.97%              |
| Geometrical features, fractal dimension      | 71.97%              |
| Gray level co-occurrence matrix              | 51.34%              |
| Moments invariants                           | 44.59%              |
| Gabor features                               | 67.36%              |
| HOG  | 62.34%              |
| LBP  | 77.07%              |
| Silva's Method                               | 67.36%              |
| Marcos's Method                              | 78.92%              |
| Features combination (without decomposition) | 80.19%              |
| Our proposed method                          | <b>86.94%</b>       |

creases the dimensionality of the representation, it appears to capture better the visual complexity of pollen grains. Our method may be further improved by using different clustering techniques to decompose layers or by performing hierarchical classification.

Table 2: Evaluation Measurements

| Method               | Precision     | Recall        | sensitivity   | specificity   | F score       |
|----------------------|---------------|---------------|---------------|---------------|---------------|
| Features combination | 81.16%        | 79.68%        | 79.68%        | 99.31%        | 79.31%        |
| Our proposed method  | <b>88.40%</b> | <b>86.95%</b> | <b>86.75%</b> | <b>99.56%</b> | <b>87.54%</b> |

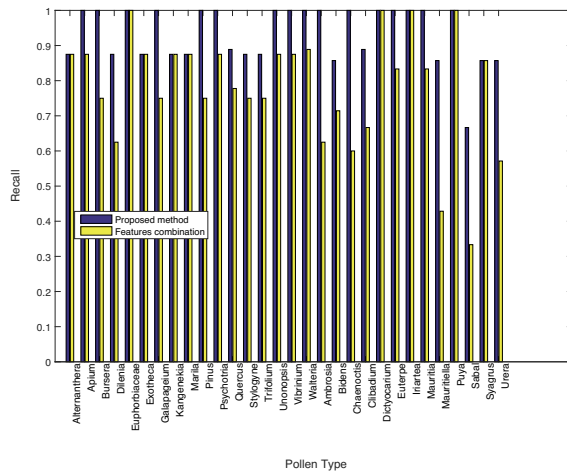


Figure 3: Recognition rate for each pollen type.

## References

- Allen, G.; Hodgson, R.; Marsland, S.; and Flenley, J. 2008. Machine vision for automated optical recognition and classification of pollen grains or other singulated microscopic objects. In *International Conference on Mechatronics and Machine Vision in Practice*, 221–226. IEEE.
- Boucher, A.; Hidalgo, P.; Thonnnt, M.; Belmonte, J.; Galan, C.; Bonton, P.; and Tomczak, R. 2002. Development of a semi automatic system for pollen recognition. *Aerobiologia* 18(3-4):195–201.
- Chica, M. 2012. Authentication of bee pollen grains in bright-field microscopy by combining one-class classification techniques and image processing. *Microscopy research and technique* 75(11):1475–1485.
- Cortes, C., and Vapnik, V. 1995. Support-vector networks. *Mach. Learn.* 20(3):273–297.
- Costa, A.; Humpire-Mamani, G.; and Traina, A. 2012. An efficient algorithm for fractal analysis of textures. In *Graphics, Patterns and Images (SIBGRAPI), 2012 25th SIBGRAPI Conference on*, 39–46.
- Da Silva, D. S.; Quinta, L. N. B.; Goncalves, A. B.; Pistori, H.; and Borth, M. R. 2014. Application of wavelet transform in the classification of pollen grains. *African Journal of Agricultural Research* 9(10):908–913.
- Dahme, G.; Ribeiro, E.; and Bush, M. 2006. Spatial statistics of textons. In *International Conference on Computer Vision Theory and Applications*, 13–19.
- del Pozo-Banos, M.; Ticay-Rivas, J. R.; Alonso, J. B.; and Travieso, C. M. 2015. Features extraction techniques for pollen grain classification. *Neurocomputing* 150: 377–391.
- Dell’Anna, R.; Cristofori, A.; Gottardini, E.; and Monti, F. 2010. A critical presentation of innovative techniques for automated pollen identification in aerobiological monitoring networks. *Pollen: structure, types and effects* 273–288.
- Dietterich, T. G., and Bakiri, G. 1995. Solving multiclass learning problems via error-correcting output codes. *Journal of artificial intelligence research* 263–286.
- Escalera, S.; Pujol, O.; and Radeva, P. 2009. Separability of ternary codes for sparse designs of error-correcting output codes. *Pattern Recognition Letters* 30(3): 285 – 297.
- Flenley, J. 1968. The problem of pollen recognition. In *Problems in Picture Interpretation*. Clowes MB, Penny JP (eds) CSIRO: Canberra, 141–145.
- France, I.; Duller, A.; Duller, G.; and Lamb, H. 2000. A new approach to automated pollen analysis. *Quaternary Science Reviews* 19(6): 537 – 546.
- Garcia, N. M.; Chaves, V. A. E.; Briceno, J. C.; and Travieso, C. M. 2012. Pollen grains contour analysis on verification approach. In *Hybrid Artificial Intelligent Systems*. Springer. 521–532.
- Guru, D.; Siddesha, S.; and Manjunath, S. 2013. Texture in classification of pollen grain images. In *Multimedia Processing, Communication and Computing Applications*. Springer. 77–89.
- Hastie, T.; Tibshirani, R.; Friedman, J.; Hastie, T.; Friedman, J.; and Tibshirani, R. 2009. *The elements of statistical learning: Data Mining, Inference, and Prediction*, volume 2. Springer.
- Hodgson, R. M.; Holdaway, C.; Zhang, Y.; Fountain, D.; and Flenley, J. 2005. Progress towards a system for the automatic recognition of pollen using light microscope images. In *International Symposium on Image and Signal Processing and Analysis*, 76–81.
- Holt, K. A., and Bennett, K. D. 2014. Principles and methods for automated palynology. *New Phytologist* 203(3): 735–742.
- Kaya, Y.; Mesut Pinar, S.; Emre Erez, M.; Fidan, M.; and Riding, J. B. 2014. Identification of onopordum pollen using the extreme learning machine, a type of artificial neural network. *Palynology* 38(1): 129–137.
- Lagerstrom, R.; Arzhaeva, Y.; Bischof, L.; Haberle, S.; Hopf, F.; and Lovell, D. 2013. A comparison of classification algorithms within the classifynder pollen imaging system. In *Proceedings of the 2013 AIP Conference*, 1559: 250–259. AIP-American Institute of Physics Publishing.
- Li, P.; Treloar, W. J.; Flenley, J. R.; and 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* 19(8): 755–762.
- Marcos, J. V.; Nava, R.; Cristobal, G.; Redondo, R.; Escalante-Ramirez, B.; Bueno, G.; Deniz, O.; Gonzalez-Porto, A.; Pardo, C.; Chung, F.; and Rodriguez, T. 2015. Automated pollen identification using microscopic imaging and texture analysis. *Micron* 68(0): 36 – 46.
- McMichael, C. H.; Palace, M. W.; Bush, M. B.; Braswell, B.; Hagen, S.; Neves, E. G.; Silman, M. R.; Tamanaha, E. K.;



and Czarnecki, C. 2013. Predicting pre-columbian anthropogenic soils in amazonia. *Proceedings of the Royal of London Society B: Biological Sciences* 281(1777).

M.Fernandez-Delgado; P.Carrion; E.Cernadas; and J.F.Galvez. 2003. Improved classification of pollen texture images using svm and mlp. In *Proceedings of international conference on visualization, imaging, and image processing*. Vol. 2.

Nguyen, N. R.; Donalson-Matasci, M.; and Shin, M. C. 2013. Improving pollen classification with less training effort. In *Applications of Computer Vision (WACV), 2013 IEEE Workshop on*, 421–426.

Ojala, T.; Pietikainen, M.; and Maenpaa, T. 2000. Gray scale and rotation invariant texture classification with local binary patterns. In *Computer Vision - ECCV 2000*, volume 1842 of *Lecture Notes in Computer Science*. Springer Berlin Heidelberg. 404–420.

Rafael C. Gonzalez, Richard E. Woods. 2006. Digital Image Processing (3rd Edition). Prentice-Hall, Inc. Upper Saddle River, NJ, USA

Rodriguez-Damian, M.; Cernadas, E.; Formella, A.; Fernandez-Delgado, M.; and De Sa-Otero, P. 2006. Automatic detection and classification of grains of pollen based on shape and texture. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews* 36(4): 531–542.

Sokolova, M.; Japkowicz, N.; and Szpakowicz, S. 2006. Beyond accuracy, f-score and roc: a family of discriminant measures for performance evaluation. In *AI 2006: Advances in Artificial Intelligence*. Springer. 1015–1021.

Ticay-Rivas, J. R.; Del Pozo-Banos, M.; Travieso, C. M.; Arroyo-Hernandez, J.; Perez, S. T.; Alonso, J. B.; and Mora-Mora, F. 2011. Pollen classification based on geometrical, descriptors and colour features using decorrelation stretching method. In *Artificial Intelligence Applications and Innovations*. Springer. 342–349.

Travieso, C. M.; Briceno, J. C.; Ticay-Rivas, J. R.; and Alonso, J. B. 2011. Pollen classification based on contour features. In *Intelligent Engineering Systems (INES), 2011 15th IEEE International Conference on*, 17–21.

Treloar, W. J.; Taylor, G. E.; and Flenley, J. R. 2004. Towards automation of palynology 1: analysis of pollen shape and ornamentation using simple geometric measures, derived from scanning electron microscope images. *Journal of Quaternary Science* 19(8): 745–754.

Zhang, Y.; Fountain, D. W.; Hodgson, R. M.; Flenley, J. R.; and Gunetileke, S. 2004. Towards automation of palynology 3: pollen pattern recognition using Gabor transforms and digital moments. *Journal of Quaternary Science* 19(8): 763–768.