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POLLIMAC II: A Modular Automated Pollen Image Classifier

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ABSTRACT – In the Philippines, identification of plant resources utilized by bees has been done mainly by manual classification using taxonomic keys and comparison with reference slides. This practice is quite tedious specially on a large number of data. Digital techniques for imaging pollen have simplified the identification process but still required time and skill. Automation of the digitized pollen can solve the need for a faster and accurate identification system. This provides better knowledge for the management of local flora and eventually the conservation and survivorship of bees. We present POLLIMAC II, an improved version of an automated pollen image classification system that uses artificial neural networks and digital image analysis. Previous version of the system could not automatically process raw images captured as inputs and provided only a limited set of classifiers. POLLIMAC II, on the other hand, has a modular framework composed of three parts namely: the input module; the feature extraction module that extracts image features; and the ANN module, which takes the features to train and learn to classify the input pollen images.

Keywords: palynology, pollen image classification, artificial neural networks

INTRODUCTION

Pollen is utilized by bees as their main protein source for nourishment and for sustaining the reproductive function of the queen. Bees have specific plant preferences for the source of pollen. The identification of plant resources utilized by bees is of great importance to the conservation and management of bee species. The accurate identification of plant species that are important to the lifecycle and to the foraging processes of specific bees in specific localities provides academics, researchers, and conservationists alike the knowledge to properly manage the flora for which the local bee colonies depend on. Knowing that not only the local bee industry relies on the proper management of the bee resources but that the diversity of the local flora depends on the activities of bees, the accurate identification of the flora resources which the local bees depend on must be one of the management and conservation activities of the people whose livelihood rely on this species. With this, the continuous mutualistic interaction between plants and bees could be preserved.

One of the processes done to identify plant species that are important to the lifecycle and to the foraging processes of bees in specific localities is the identification of pollens that the local bee colonies usually use for their honey making. Several researches from different parts of the Philippines have been

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performed in identifying bee pollen forage such as in Bohol (Deyto et al., 2009), Pagbilao, Quezon (Almazol and Cervancia, 2013), Davao (Cunanan-Deyto et al., 2012) and Palawan (Manila-Fajardo and Gonzales, 2010). However, these palynological studies have relied on manual classification of pollens using taxonomic keys and comparisons with reference slides of various plant species. This has been quite a tedious and lengthy process in identifying plant sources. While the advent of digital techniques for imaging pollen simplified the otherwise laborious manual process, identifying pollen types from hundreds of digitized microscopic images gathered still required time and skill. There is, however, a demand for a rapid honey source identification system from the beekeeping and related industries, and the solution is to automate the classification from the digitized slides.

A lot of computer-based and automated systems were designed solely for the purpose of pollen identification and classification. Several approaches were already designed to reliably and accurately classify plant pollen, most of which employed image processing and analysis by extracting image features such as edge statistics, pixel statistics, brightness and color-based features (Rodriguez-Damian, 2004), size, shape, and texture (Zhang and Wang, 2004) from the raw image, transforms of images, or even transforms of transforms of image (Orlov et al., 2009). The use of Artificial Neural Network (ANN) together with image processing and analysis had already been found to be successful when used to build automated pollen classification systems (Baladad, 2010). The ANN was built into the previous version which provided a classification accuracy of 78.70%.The current effort of improving the system is to allow for the future improvement of the classification accuracy by ANN or other automated classification schemes.

This study is part of a collaboration with the University of the Philippines Los Baños (UPLB) Bee Program and the Institute of Computer Science (ICS) at UPLB on automated classification of pollen from bee plants (plants pollinated by bees) using digital image analysis and advance intelligent systems. There were already outputs on initial collaborative efforts in this study but there is still a need to develop and improve on a system that bee researchers could really use.

In 2011, Encinas et al. developed an automated classification system for pollen images called POLLIMAC which stands for POLLen IMAge Classifier. POLLIMAC was developed to provide a web-based interface of an ANN-based pollen image classifier.

This study focused on the current state and the improvements for POLLIMAC in sustaining the collaboration of UPLB Bee Program and ICS. Named POLLIMAC II, this study aimed to lay out a modular framework consisting of three modules namely, the input module, feature extraction module and the ANN module. Specifically, we also aimed to allow researchers to input pre-segmented or raw data images, to allow researchers to choose the segmentation algorithm to be used for segmenting raw input images, and to integrate a modular implementation of Zernike and image histogram extraction feature models.

METHODOLOGY

In order to establish an improved version of POLLIMAC, a modular framework was laid out. The framework consisted of three modules namely: (1) input module, (2) feature extraction module, and

(3) ANN module. Figure 1 shows the flow of processes occurring in the classification of pollen images. The detailed description of each module is discussed in the succeeding subsections of this paper.

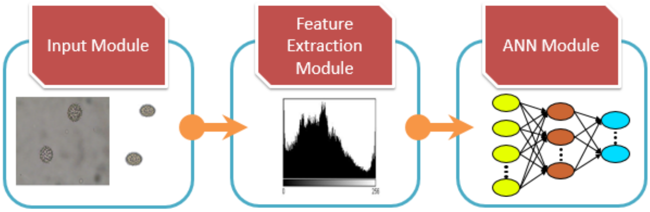


Figure 1. The three primary modules of POLLIMAC II and the schematic of their interdependency with one another.

2.2 Input Module

The input module is where the automated segmentation of input pollen images is being performed. Previous version of POLLIMAC requires the user to pre-process raw images before submitting them as input to the system. Pre-processing was done by manually segmenting individual pollen from raw microscopic images using a separate image editor (e.g. Microsoft paint, Adobe Photoshop). In the modularized version, the user has the option to submit raw image data and let this module perform the automated segmentation to extract individual pollen images.

2.2.1 Input Image Data

Four families of bee-pollinated plants were considered in this study. More so, two species from each family were selected, specifically *Bidens pilosa L.* (spanish needle) and *Tagetes erecta L.* (marigold) from the family Compositae, *Cajanus sp.* (pea) and *Crotalaria sp.* (rattlepod) from the family Leguminosae, *Panicum sp.* (grass) and *Zea mays L.* (corn) from the family Graminae, *Solanum lycopersicum L.* (tomato) and *Solanum melongena L.* (eggplant) from the family Solanaceae.

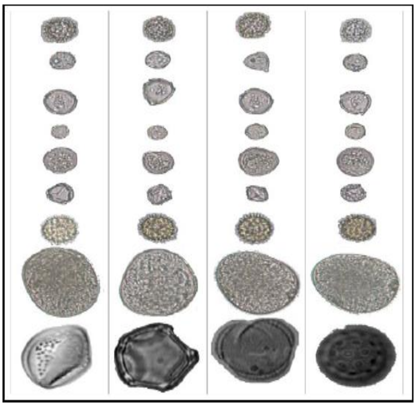
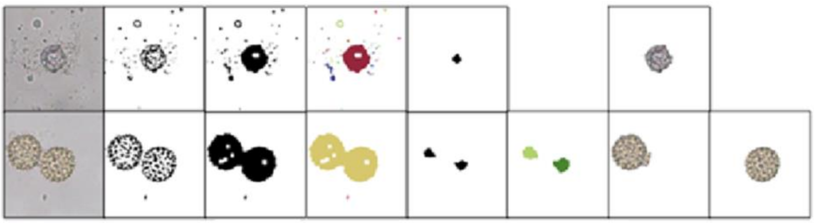


Figure 2. Sample pollen images used, from top to bottom: *Bidens pilosa L.*, *Cajanus sp.*, *Crotalaria sp.*, *Solanum lycopersicum L.*, *Panicum sp.*, *Solanum melongena L.*, *Tagetes erecta L.*, *Zea mays L.* and unknowns.

Figure 2 shows sample images that were used in the study. Images of pollen species not belonging to any of the species above were also taken. These images were labeled as unknowns and were used as the ninth class used in the training of ANN. The unknown labels introduce what we call negative examples during the ANN training and is necessary so that the ANN will learn to output pollens that it does not know. The known labels in the eight pollen classes are what we call positive examples. Without the unknown labels, the ANN will be forced to label a future-encountered unknown class as one of the eight classes, which will render the ANN's accuracy to fall down. Thus, the unknown is a catch-all class for pollens that do not fall to any of the eight classes that were considered in this study.

2.2.2 Automated Segmentation

Automated segmentation is performed on input images to separate individual pollens from the background image and from among other pollens in the same image. A sequence of image binarization, image filtering, pollen detection, and pollen extraction is performed on all input images to complete the entire process of the automated segmentation. Figure 3 shows the process how individual pollens were extracted from raw images. The first row of images shows how automated segmentation is done for raw image containing only one pollen; the second row shows an automated segmentation process for a raw image containing more than one pollen. The details of each step are discussed in the succeeding subsections.



(A) (B) (C) (D) (E) (F)

Figure 3. The sequence of image manipulation and processing in order to extract individual and multiple pollens from the input images as (A) raw image, (B) binarized image, (C) filtered image, (D) pollen detection, (E) separation for multiple pollen images and (F) pollen extraction.

Image binarization converts an image into a two-dimensional array of binary digits (1’s and 0’s) separating the foreground pixels (all 1’s) from the background pixels (all 0’s). The resulting image is called a binarized image.

In image filtering, the binarized image undergoes a digital filtering process to clean the noise obtained from binarization. To correct for the noise in the binarized image, the process of digital binary dilation was used to fill gaps between pixels within the object while binary erosion was used to remove pixels that most likely do not belong to any object in the image.

The process of Pollen Detection consists of three processes: pollen separation, multiple pollen detection, and separation of multiple pollens. These processes are discussed as follows:

Pollen Separation: From the binarized image, the 8-Connected component method was used to separate possible pollen objects in the image from the binarized image. All components that were above the minimum component size were candidates for pollen extraction. This requirement was needed to avoid objects that most likely not a pollen.

Multiple Pollen Detection: Using continuous binary erosion, detection of multiple pollens in the image is needed to know if further processing is needed. Continuous erosion was used to solve the problem of pollen objects that are too close to each other or are touching one another and are considered as one object by the 8-Connected component method. Once the pollens have been detected or if only one pollen is detected, the image will already be subjected to pollen extraction.

Separation of Multiple Pollens: In images that contain multiple pollens, the center and radius of each pollen was obtained. The center was obtained using the center of mass method while the radius was obtained from the maximum lengths of line segment from the computed center to the pollen edges.

Finally, the process of pollen extraction was done using a border following algorithm. The output of this method is the background-less image of the detected pollen objects. For images that contain two or more pollens, the numbers of detected pollens are outputted by the process.

2.3 Image Feature Extraction Module

Two image features, namely image histogram and Zernike feature, were taken from images used in the study. Extracting the image histogram from an image results to a total of 256 numerical values while extracting the Zernike feature results to a total of 49 numerical values resulting to a sum of 305 extracted features for every single image. These 305 numerical values were then presented as inputs to the classifier.

2.3.1 Image Histogram

For an 8-bit grayscale image, a histogram is a graph showing the frequency distribution of pixels in an image at every intensity value from 0 to 255 summing up to a total of 256 different possible intensities. Image histogram provided 256 numerical values as inputs to the classifier.

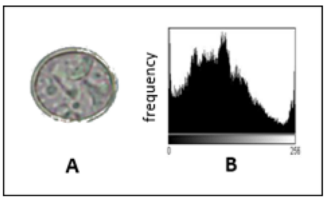


Figure 4. Sample image histogram (B) of a pollen image (A)

2.3.2 Zernike Feature

Zernike features are the coefficients of the Zernike polynomial approximation of a particular image. This polynomial is generated to approximate an image to some fidelity and the coefficients of the polynomial are used as descriptors of the image.

Zernike polynomials are a series of polynomials defined within a unit circle. It is composed of three elements: (1) normalization coefficient, (2) radial polynomial component, and (3) sinusoidal angular component.

Zernike polynomials are used to compute for Zernike moments. Since Zernike features are defined over the unit circle, it is necessary to convert a rectangular region of each image to a unit circle for the calculation of Zernike moments (Boland, 1999). To implement this method, an image is modeled over a user-selected circular region of variable-diameter, centered on the axis of measurement. The center of mass (COM) for each image was calculated and was used to define the center of the pixel coordinate system. Only pixels that are within the unit circle of the resulting normalized image f(x,y) were used for subsequent calculations. The Zernike moments Z_{nl} for an image were then calculated using

Equation 1. Formula for computing the Zernike moments

where $x^2+y^2 \leq 1$, $0 \leq l \leq n$, n-l is even, f(x,y) describes the intensity values of the normalized image and $V_{nl}*$ is the complex conjugate of a Zernike polynomial of degree n, l is the angular dependence (frequency), and ρ is the radius.

Equation 2. Formula for setting-up the Zernike polynomial

In this study, Zernike features up to order 12 ($n \leq 12$) were computed. A total of 48 numerical values were obtained which were used as additional inputs to the classifier.

2.4 ANN Module

An ANN was designed to process the numerical values obtained from image feature extraction. A feed-forward neural network for classifying pollens from eight plant species and the unknowns were trained using the back-propagation algorithm. The back-propagation algorithm is a form of supervised training method wherein the ANN is provided with the sample inputs with their correct respective classes. A total of 305 extracted image features (numerical image descriptors) were used as input to the ANN. Three data sets were respectively used for the training, the validation, and the testing of the ANN. The data in the training set were used to train the ANN while those in the validation set were used to determine when to stop the training process. Knowing to stop the ANN training at the proper time is important to the generalization capabilities of the ANN as over training, it will memorize the data in the training set. A total of 540 images were used, equally representing the eight plant species dubbed as the positive examples with an added “unknown” class that acted as the negative examples. Each class contains 60 images, 60% of which (or 36 samples) were randomly chosen to belong in the training set, 20% (12 samples) in the validation set, and 20% (12 samples) in the testing set. Since the images at each class do not vary in terms of their visual appearance, the 12 samples in the testing set for each class is already enough to measure the accuracy metric of the ANN. Table 1 shows the distribution of images used for training, validation, and testing.

Table 1. Number of Images used by the ANN in Training, Validation and Testing

POLLEN CLASS	NUMBER OF IMAGES USED		
	TRAINING	**VALIDATION**	**TESTING**
Bidens pilosa L.	36	12	12
Cajanus sp.	36	12	12
Crotalaria sp.	36	12	12
Solanum lycopersicum L.	36	12	12
Panicum sp.	36	12	12
Solanum melongena L.	36	12	12
Tagetes erecta L.	36	12	12
Zea mays L.	36	12	12
Unknown	36	12	12
Total images	**324**	**108**	**108**

All the input images used were of Joint Photographic Experts Group (JPEG) format with a standard size of 300 by 300 pixels. As indicated in Table 1, 36 images per pollen class were used in the training, 12 images per pollen class were used for validation, and the remaining 12 images per pollen class were used for testing.

These were the different parameters used by the ANN whose values can be altered in order to create a neural network file for classification:

1. Number of Input Nodes
   The input nodes of the ANN are the ones that accept input values.

2. Number of Hidden Nodes
   The Hidden nodes of an ANN occur between the input and output nodes.

3. Number of Output Nodes
   The output nodes are final nodes of an ANN that produce the output for the neural network.

4. Learning rate
   The learning rate specifies how fast the ANN will learn. This is usually a value around one, as it is a percent.

5. Momentum
   The momentum specifies how much of an effect the previous training iteration will have on the current iteration. The momentum is also a percent, and is usually a value near one.

6. Epoch
   One training interval; synonymous with iteration.

RESULTS AND DISCUSSION

Web User Interface

The resulting web-based user interface (UI) was developed using Java Server Pages (JSP) and Java. The use of Java provided ease for the integration with Java Object Oriented Neural Engine (JOONE), a Java-based neural network framework, which was used for the implementation of the classifier.

Figure 5 shows the developed web-based UI with the implemented modularity. A user who wants to classify an image or set of images has to go to five steps as shown. Step 1 allows the user to select the input images of his or her liking. The images to be uploaded can be raw images or pre-segmented images.

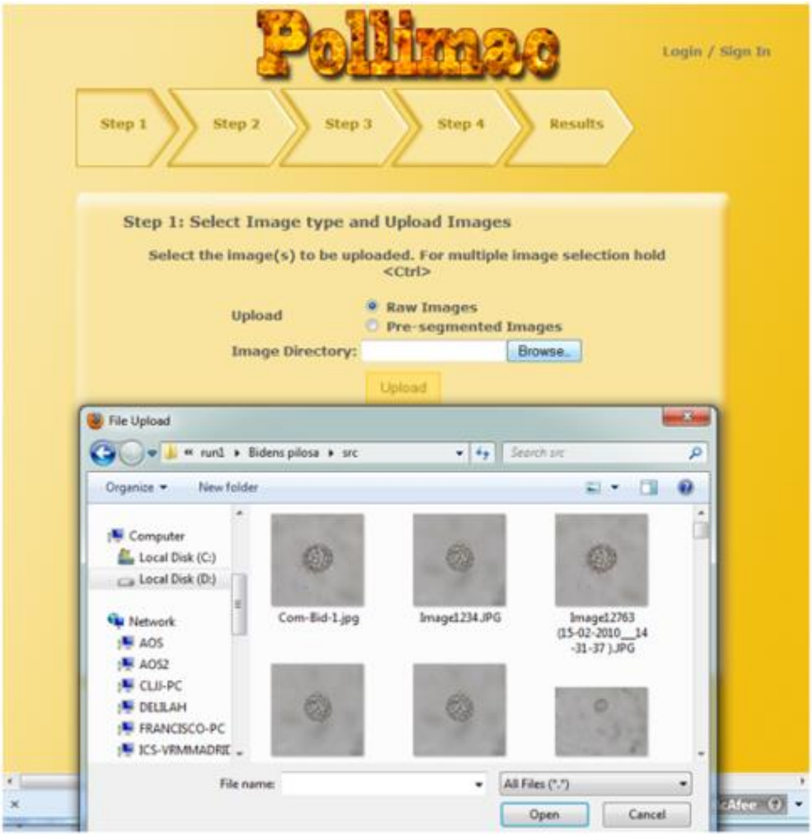


Figure 5. Users can opt to upload pre-segmented data or raw data and use the automated segmentation module.

In step 2, the user is allowed to choose the segmentation algorithm to be used. Shown in Figure 6, there are currently two segmentation algorithms that can be used. Step 2 is done if the image or set of images is not yet pre-segmented otherwise we proceed to step 3.

Figure 6. Choose from a list of existing image segmentation algorithms.

Step 3 allowed a user to view the segmented images that was subjected to a segmentation algorithm in step 2. The images, by default, were all selected for classification but the user can still unselect images that the user does not want to be classified in step 4. Figure 7 shows the UI for this step.

Figure 7. From the output of the segmentation algorithm, choose from a list of segmented images to be classified.

The selected segmented images in step 4 will then be classified using the ANN module. The results step lists the input images followed by the classification. As an example, using Figure 8, image 12 with filename Com-Tag-1.jpg.00.jpg was classified as *Tagetes erecta L.* with 97% confidence.

Figure 8. Viewing the result of classification using POLLIMAC II.

Results of Classification

Table 2 shows the result of the classification using only the image histogram as input feature to the ANN with a single hidden layer of 200 nodes, learning rate set to 0.1, and momentum set to 0.1. Using the provided parameters, it can be observed that *Cajanus sp.*, *Zea mays L.*, and the unknowns were 100% correctly classified over the twelve (12) test images per pollen class. The species *Solanum melongena L.* obtained the lowest classification with 8.33% or 1 input image classified over the twelve input images.

Table 2. Number of correct classifications per pollen species classified by the ANN trained with a single hidden layer of 200 nodes, 0.1 learning rate and 0.1 momentum values over the testing set.

POLLEN CLASS	PERCENTAGE CORRECT CLASSIFICATION	OFCORRECT CLASSIFICATION /TOTAL IMAGES
Bidens pilosa L.	83.33	10/12
Cajanus sp.	100.00	12/12
Crotalaria sp.	50.00	6/12
Solanum lycopersicum L.	91.67	11/12
Panicum sp.	91.67	11/12
Solanum melongena L.	8.33	1/12
Tagetes erecta L.	83.33	10/12
Zea mays L.	100.00	12/12
Unknown	100.00	12/12
TOTAL	**78.70**	**85/108**

Upon the introduction of the Zernike feature, the ANN with a single hidden layer was found to have good results if learning rate was set to 0.4 and momentum to 0.3. Moreover, it was noted that varying the number of nodes in the hidden layer has significant effect on the overall accuracy of the classifier. Further manipulation of the number of nodes in the hidden layer while keeping the learning rate to 0.4 and momentum to 0.3 yielded to the following results shown in Table 3.

Table 3. Number of correctly classified images per species given twelve (12) input images as the result of ANN using Histogram and Zernike Feature with varying number of Nodes in the Hidden Layer.

POLLEN CLASS	**NUMBER OF NODES**					
	100	**125**	**150**	**175**	**200**	**225**
Bidens pilosa L.	10/12	10/12	10/12	10/12	10/12	10/12
Cajanus sp.	11/12	11/12	11/12	11/12	11/12	11/12
Crotalaria sp.	1/12	1/12	4/12	2/12	2/12	2/12
Solanum lycopersicum L.	6/12	8/12	6/12	6/12	4/12	5/12
Panicum sp.	10/12	11/12	11/12	11/12	11/12	11/12
Solanum melongena L.	4/12	4/12	7/12	5/12	4/12	4/12
Tagetes erecta L.	10/12	10/12	10/12	10/12	10/12	10/12
Zea mays L.	12/12	12/12	12/12	12/12	12/12	12/12
Unknown	12/12	12/12	12/12	10/12	12/12	12/12
Total Correct Classification in Percentage (%)	**70.37**	**73.15**	**76.85**	**71.30**	**70.37**	**71.30**

Based from Table 3, a hidden layer with 150 nodes for an ANN with learning rate equal to 0.4 and momentum equal to 0.3 can achieve an average accuracy of at most 76.85%. This is 1.85% lower compared to the accuracy of Baladad's (Baladad, 2010) initial design for a pollen image classifier. On the other hand, results for *Solanum melongena L.* was significantly improved using Zernike features. Both feature extraction techniques have very low accuracy for *Crotalaria sp.*

A Receiver Operating Characteristic (ROC) curve was done to analyze the results further for Histogram feature. The area under the ROC curve characterizes the quality of a forecast system by describing the system's ability to anticipate correctly the occurrence or non-occurrence of pre-defined 'events' (Mason and Graham, 2002). Figure 9 shows the plot for a multiclass ROC since the input images need to be classified under nine pollen classes.

The y-axis represented the True Positive Rate (TPR) while the x-axis represents the False Positive Rate (FPR). The TPR is the percentage rate of test images correctly identified by the system to its true classification out of the nine pollen classifications. The FPR is the percentage rate of test images where the system marks an image to be correctly identified when it is not the case.

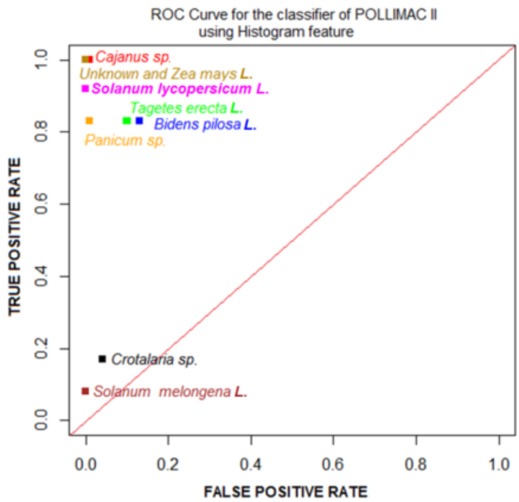


Figure 9. ROC Curve for the classifier with Histogram feature.

Figure 9 shows that pollen images for *Zea mays L.* and unknown pollen classes have a TPR of 1.0 and FPR of zero. It means that all the images under those pollen classes were correctly identified. The pollen classes for *Cajanus sp.*, *Solanum lycopersicum L.*, *Tagetes erecta L.*, *Bidens pilosa L.*, and *Panicum sp.* show high TPR values with varying low FPR values. It can be noted that all of them have TPR values no lower than 0.80 and that their FPR values are all less than 0.20. While seven out of the nine pollen classes displayed high values of TPR, it can be observed that *Solanum melongena L.* and *Crotalaria sp.* showed TPR values lower than 0.20. This means that majority of the input images for both *Solanum melongena L.* and *Crotalaria sp.* pollen classes were not correctly identified. However, it can also be noted that both *Solanum melongena L.* and *Crotalaria sp.* pollen classes have lower FPR values as compared with *Tagetes erecta L.* and *Bidens pilosa L.*

CONCLUSION AND RECOMMENDATIONS

In this study, we were able to lay out a modular framework consisting of three modules namely the input module, feature extraction module and ANN module that can support for later improvements of the pollen classification system. Because of this modular framework, an improved version of POLLIMAC was developed to allow for easy integration of future improvements of the automated classifier. This will provide palynologists continued software support to further improve software-assisted pollen classification.

Using POLLIMAC II, bee researchers can automatically classify pollen images and test the output of the classifier itself while at the same time, computer science studies and explorations on better image segmentation algorithms and other additional feature extraction techniques can continue.

In the event that better segmentation algorithms are developed, they can easily be integrated to POLLIMAC II through the first module. On the other hand, additional feature extraction techniques can also be explored and incorporated easily to the feature extraction module of POLLIMAC II. The modular framework of POLLIMAC II therefore provided a very good and easy avenue for future studies to improve the accuracy of the classifier either by introducing a new segmentation algorithm or additional feature extraction techniques without having to create a new classification system from scratch.

There are also ongoing efforts to improve the automated segmentation and integrate two image feature extraction techniques namely: Median-Binary Partition and Haralick features. More training image features are recommended to increase the accuracy of the classifier. Continued improvement of the web interface could also be pursued and the possible extension of the classification system not only for pollens but to other microscopic data such as fungal spores.

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STATEMENT OF AUTHORSHIP

The first author is the project leader during the extension and completion of the project. The second author is the main web developer. The first two authors were also the lead writers of the paper. The third and fourth authors were former students who developed modules for automated segmentation and classification. The fifth author was the former project leader, initiated this study, and advised most of the students who worked on this project. The sixth author worked on the initial design and implementation of the ANN module using the histogram feature. The eighth author guided the group regarding the ANN module and writing of the paper. The seventh, ninth, and last author were collaborators from the UPLB BEE Program who helped in designing of the system, gathering of data, and writing of the paper.

REFERENCES

Almazol A.E. and C.R. Cervancia (2013). Floral Biology and Pollination of Three Mangrove Species (Aegiceras floridum Roem. & Schults., Scyphiphora hydrophyllacea Gaertn. f., and Xylocarpus granatum Koen.) in Pagbilao Mangrove Forest, Quezon Province, Philippines. Journal of Nature Studies 12 (1): 39-47.

Baladad J.S. (2010). Performance of Pollen Image Classifiers with Image Histograms and Artificial Neural Network Inputs. Master Thesis, Institute of Computer Science UPLB.

Boland M.V. (1999). Quantitative Description and Automated Classification of Cellular Protein Localization Patterns in Fluorescence Microscope Images of Mammalian Cells. Doctors dissertation, Carnegie Mellon University.

Cunanan-Deyto R.A., A.C. Manila-Fajardo and C.R. Cervancia (2012). Pollen Contents of Apis mellifera Linn. Honey from Davao City, Philippines. Journal of Nature Studies 11 (1&2): 96-102.

Deyto R.C., G. Casabal and C.R. Cervancia (2009). Pollen Sources of Apis dorsata Fabr. in Bilar, Bohol. Paper presented during the 15th Annual BEENET Conference and Technofora. 22-26 July 2009, Siquijor.

Encinas J.E.I., A.J. Jacildo, J.S. Baladad, J.P. Pabico, C.R. Cervancia and A.C. Fajardo Jr. Web User Interface of an Artificial Neural Network Classifier for Pollen Images. Paper presented in the 17th BEENET Conference and Techno-fora, Development Academy of the Philippines, Tagaytay City, Cavite, 18-20 August 2011.

Manila-Fajardo A.C. and A.K.B.M. Gonzales (2010). Pollen Sources of Apis dorsata Fabr. in the Mainland Palawan Philippines. Phil. Ent . 24(2):37-149.

Mason, Simon J. and N.E. Graham (2002). Areas beneath the relative operating characteristics (ROC) and relative operating levels (ROL) curves: Statistical significance and interpretation. Quarterly Journal of the Royal Meteorological Society (128): 2145–2166.

Orlov N., L. Shamir, T. Macura, J. Johnston, D.M. Eckley, and I.G. Goldberg (2009). WND-CHARM: Multi-purpose Image Classification Using Compound Image Transforms. Image Informatics and Computational Biology Unit, University of Cambridge.

Rodriguez-Damian M., E. Cernadas, A. Formella and R. Sa-Otero (2004). Pollen Classification Using Brightness-based and Shape-based Descriptors. Proceedings of the 17th International Conference on Pattern Recognition. Vol. 2, pp. 212- 215.

Zhang Y. and R. Wang (2004). A Combined method for texture analysis and its application. Springer-Verlag.

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