World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:17, No:7, 2023

Comparison of Machine Learning and Deep Learning Algorithms for Automatic Classification of 80 Different Pollen Species

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Abstract—Palynology is a field of interest in many disciplines due to its multiple applications: chronological dating, climatology, allergy treatment, and honey characterization. Unfortunately, the analysis of a pollen slide is a complicated and time consuming task that requires the intervention of experts in the field, which are becoming increasingly rare due to economic and social conditions. In this context, the automation of this task is urgent. In this work, we compare classical feature extraction methods (Shape, GLCM, LBP, and others) and Deep Learning (CNN and Transfer Learning) to perform a recognition task over 80 regional pollen species. It has been found that the use of Transfer Learning seems to be more precise than the other approaches.

Keywords—Image segmentation, stuck particles separation, Sobel operator, thresholding.

I. Introduction

POLLEN identification has many uses such as paleoecology, forensic science, chronological dating, climatology, honey characterization, and even petroleum exploration. Depending on the application, the palynologist will typically take a biological sample (airborne pollen, honey, anther), to which he will apply a physicochemical treatment (acetolysis, staining, centrifugation) to highlight the phenotype of the pollens present in the sample and thus, facilitate their identification [1]. Then, the palynologist will manually count the pollens with an optical microscope using a low resolution (x40). Once the counting is completed, he will use a higher resolution (x100) to proceed to the identification of the pollens. Tens of thousands of pollens are present in the samples, and many pollen species are visually similar. These are the reasons why a palynological analysis is a time consuming, complex and expensive task. To reduces the time, and the cost of palynological analysis, since Flenley (1968), many publications have proposed the use of algorithms and image processing tools to automate this practice [2]. Many works have proposed the use of classical image descriptors such as those of shape (area, circularity, Hue moment), contours (Fourrier Elliptic descriptor, Freeman chain code), or textures (Haralick coocurence matrix, Gabor filter) [3]–[11]. In addition to the classical attributes, descriptors specially designed for the pollen identification task have been reported in the literature [12]–[15]. The results reported by these works show that better performance is obtained by combining them with classical attributes. Other studies have used more sophisticated acquisition systems such as the electron microscope, confocal microscope or the classyfinder to improve species identification rate [16]–[18]. Finally, Deep Learning methods (CNN, RNN, Transfer Learning) have been investigated, this approach has shown higher classification rates than the previous ones [21]–[23].

In this work, we make a comparative study between classical feature extraction method and Deep Learning methods to perform a pollen recognition task on 80 regional species. First, we present the method we used to locate and extract pollens from the image. Then comes the pollen grain dataset on which we performed our tests. In a third step, we introduce the image descriptors we used to characterize the pollen images. In the fourth part, the Deep Learning methods we applied are described. Finally, a comparison between the results obtained using classical feature extraction methods (Shape, GLCM [19], LBP [20], and others) and Deep Learning (CNN and Transfer Learning) is discussed in the fifth section.

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II. Segmentation

As shown in Fig. 1, the pollens are clearly distinguishable as the background color is predominant and uniform. To localize and segment the pollen, the RGB color images were converted to HSV images [24] and Otsu threshold algorithm [25] was applied to the resulting saturation channel (Fig. 2).

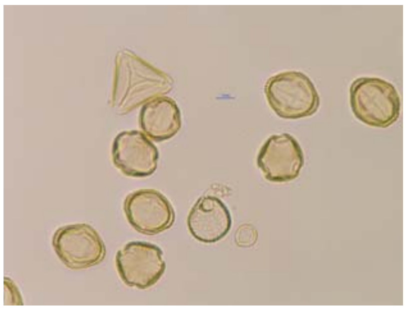

Fig. 1 Example of a pollen slide image from an optical microscope

After segmentation, a dataset (Fig. 3) containing 1,505 pollen grains images of 80 different species is obtained with approximately 20 to 40 examples by class.

III. Feature Extraction Approach

In this study, three types of features were tested:

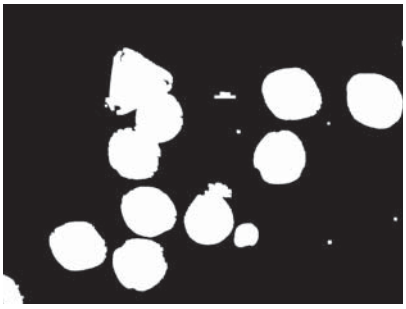

Fig. 2 Example of a pollen slide image thresholded with the Otsu method

A. Shape and Area Features

These features characterize the morphological properties of the region occupied by the pixels of a pollen grain.

In this study, we were interested in the shape index, Area, Perimeter, Extent, Compactness, Circularity, Solidity, Extent, moments, scale invariant, central, Hue and Zernike moments [26], [27].

B. Dimensionality Reduction

Dimensionality reduction transforms data in high-dimensional space to a low-dimensional representation that retains the few interesting properties of the original data. In this category of features we tested: Principal Component Analysis (PCA), Kernel PCA, and Independent component analysis (ICA).

C. Texture Features

The texture of the exine of pollen is one of the most used characteristics by palynologists in their identification process. In Fig. 5, we see that for some pollen species this criterion is discriminating. Each species in Fig. 5 has a specific exine that allows them to be distinguished visually without the need for additional information.

There are different mathematical frameworks used to describe a texture. However, three main characterization approaches can be highlighted.

1) Deterministic Approach: The structural deterministic approach uses the patterns present in a texture and their repetition to characterize it. It is used for the description of macro textures. We have not been interested in the deterministic approach, as pollens are natural elements without strict patterns.

2) Stochastic Approach: The stochastic approach uses the existing statistical relationships between each pixel and its neighborhood to characterize a texture. Among the stochastic methods that we have used, we find: First order statistical attributes (variance, skewness, etc.), second order (GLCM) and higher order (LBP, LTP,MB-LBP) and Radiomics.

3) Spatio-Frequential Approach: The spatio-frequential approach is interested in the frequencies of the interactions existing between the different pixels or the different regions of an image. We have chosen to use Gabor filters to evaluate this approach [28].

Fig. 3 A dataset containing 80 pollen species

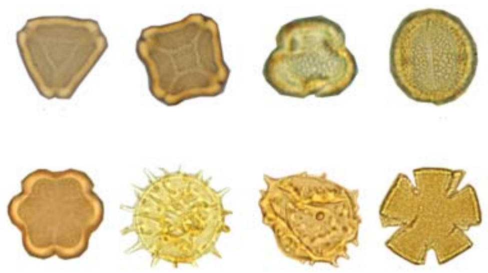

Fig. 4 Example of pollen shapes

Fig. 5 Example of pollen texture

IV. Deep Learning Approach

In addition to the classical feature extraction approach, we compared different Deep Learning based methods. In the experiments we have conducted, three different convolutional neural network architectures have been tested: Daood et al. [21], NasNetMobile, and NasNetLarge [32]. Because, the network has been specially designed for pollen identification and as for now, NASNet has the best performance in object identification among the networks proposed by the Keras library.

Each network receives an input image of fixed size. Daood et al.'s [21] network, NASNet and NASNetMobile receive, respectively, input images of dimensions: 273x273, 331 x 331, and 224 x 224. Also, the images of the pollen datasets were resized by the same factor and then placed at the center of an image of equal size to the input of the used network to respect this constraint. The image sets were then artificially increased by applying 3 rotations (90 °, 180 ° and 270 °) and then transposing all images. The dataset was thus increased from a size of 1,505 to 12,040.

V. Experimentations and Results

A. Features Extraction Approach

Once the set of features was extracted, the best ones were selected using Hall's CFS method [30]. Then they were evaluated in cross-validation. The dataset was randomly partitioned into ten groups of equal size and Multi-Layer Perceptron [29] learning was performed on nine groups while the remaining group was used for testing. This process was repeated so that each of the ten groups was tested. In these experiments, the number of hidden layer neurons was empirically set to 128 and the Adam method was used to train the neural network [31].

TABLE I
Identification Rate Obtained Using Features Extraction Methods

Features	Max Identification Rate (Best Descriptor)
Shape Index	1.55%
Zernike Moments	7.59%
PCA, Kernel PCA, ICA	43.1% (PCA)
Region descriptors	40,35%
GLCM	78.58%
Radiomics	79.32%
LBP, LTP,MB-LBP	80.18 % (LBP)
First order statistics	62.15%
GABOR	77,19%
Combinaison	91.04% (LBP+GABOR)

The results obtained using the classical approach are presented in Table I.

In the case of classical image descriptors (Table I), it was concluded that the local binary patterns provide a better characterization of pollens. Features were also combined by groups of two. The combination that achieved the highest score was LBP+GABOR. An identification rate of 91,04% was obtained for the 80 pollen species treated. Each of these methods extracts different information that was found to be complementary in the context of the description of pollen elements. Local binary patterns exploit the microscopic randomness of the texture to characterize it, while Gabor filters use directivity and directional patterns.

B. Deep Learning Approach

Compared to the tests performed with manual feature extraction, we did not test all the networks in cross-validation, because training a network requires significant hardware resources. A test set composed of 10% of the images was randomly constituted and used for testing the networks. The networks with the best performance were tested in cross-validation to confirm their effectiveness. Due to the large number of parameters (133 million) in the full NASNet version, only the last 818 layers were trained. The networks with the best performance on the dataset were tested in cross-validation to confirm their effectiveness. This is the maximum number of layers we can train with our hardware configuration (2 X NVIDIA Tesla V100).

a) Notation
: We have chosen to use the following notation to present the results of our tests.

- **X LL (X Last Layers)** Only the last X layers of the network have been trained
- **AL (All Layers)** All layers of the network have been trained.
- **FC (Fully Connected)** Only fully connected layers have been trained
- **CV (cross-validation)** The network has been tested in cross-validation

In Table II, the different identification rates achieved using the NASNet architecture are shown. We find that the rates

TABLE II
IDENTIFICATION RATE OBTAINED USING DEEP LEARNING

Used Method	Identification Rate
CNN Daood et al.	69.46%
NASNetMobile (FC)	70.01 %
NASNetMobile (AL)	90.20 %
NASNetMobile (TL + AL + VC)	83.98 %
NASNet (TL + FC)	76.95 %
NASNet (TL + 819LL)	91.88 %
NASNet (TL + 819LL +VC)	93.11 %

achieved using the lite version NASNetMobile are lower. This is mainly due to two factors: the size of the input of NASNetMobile forces an important resizing of the input image, so some visual information is lost. In addition, the number of parameters (5,330,571) and the significantly lower performance in object identification with ImageNet justify that the light network characterizes the pollens less effectively. Among the results obtained using the full version, we notice that the best results (91.88%) were obtained by training the last 819 layers of the network (TL + 819LL). We notice that the identification rate obtained by training only the fully connected layers (TL + FC) is significantly lower than the one obtained by training the last 819 layers. This shows that even if the network has a general capability in object recognition, there is a need to adapt the convolutional network filters to pollen images. Finally, the cross-validation test achieved an identification rate of 93.11% and confirmed that the deep learning approach is more efficient than the classical features extraction approach.

The generalization capability of NASNet is excellent. The network has 88,949,818 parameters. This number is much higher than the 1,505 examples we used for training. Moreover, it is accepted that the capacity of a neural network is sufficient to store an entire data set. And even optimization on randomly labeled data sets is simple. This generalization is possible because the network is pre-trained on the ImageNet dataset. Thus, it could acquire an object identification capability superior to human vision.

VI. CONCLUSION

In this work, we performed an exhaustive comparison of different identification methods. The pollen grains present in the pollen slide images were detected and extracted using Otsu thresholding. A characterization phase was then initiated, during which the descriptive characteristics of the pollen grains were extracted using several image analysis algorithms. From this exploration, we have found that the combination of region attributes, co-occurrence matrices, local binary patterns and Gabor filters better characterizes pollen grains. Each of these methods provides different information that in the context of the description of pollen elements proves to be complementary. Recognition rates of 91.04% were achieved for the 80 pollen species collected from flowers. Finally, an identification rate of 93.11% for flower pollens was obtained by training the NASNet neural network after transfer learning via the ImageNet dataset. This is the best identification rate obtained in this work.

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