# Pollen Grain Recognition Using Deep Learning

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**Abstract.** Pollen identification helps forensic scientists solve elusive crimes, provides data for climate-change modelers, and even hints at potential sites for petroleum exploration. Despite its wide range of applications, most pollen identification is still done by time-consuming visual inspection by well-trained experts. Although partial automation is currently available, automatic pollen identification remains an open problem. Current pollen-classification methods use pre-designed features of texture and contours, which may not be sufficiently distinctive. Instead of using pre-designed features, our pollen-recognition method learns both features and classifier from training data under the deep-learning framework. To further enhance our network's classification ability, we use transfer learning to leverage knowledge from networks that have been pre-trained on large datasets of images. Our method achieved ≈94% classification rate on a dataset of 30 pollen types. These rates are among the highest obtained in this problem.

## 1 Introduction

The identification of pollen grains underpins the field of Palynology, which is the study of pollen grains, spores, and some types of diatoms [1]. Palynology is a valuable tool to many applications. For example, by analyzing fossil pollen found in soil extracted from the bottom of ancient lakes, ecologists can map past climate dated over thousands of years [2]. Because some pollen types may only exist in certain geographical locations, forensics scientists use pollen found in crime scenes to geolocate suspects [3]. Interestingly, pollen also helps the petroleum-exploration industry map potential oil fields [4].

In many palynology applications, scientists build statistical distributions of pollen species, a task done by trained operators who identify and count pollen grains seen under a microscope. Common identifying attributes used include shape, symmetry, size, and ornamentation [5,6]. Counting pollen can take months to complete, sometimes occupying operators for some 16 h a week.


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This time-consuming step in palynology could be reduced from months to a few hours by an automated identification system [1].

There are three main groups of approaches to palynology automation. *Morphological* methods measure visual characteristics such as shape [2,7,8]. Treloar et al. [2] measured grain's roundness, perimeter, and area, which were input into a Fisher linear discriminant for classifying 12 types of pollen. Xie and OhEigeartaigh [9] measured 3-D geometrical features, radial and angular components from a voxel representation of pollen grains. They classified 5 types of pollen using support vector machine. Garcia et al. [8] used the changes along a grain's contour to train a Hidden Markov Model (HMM) for classification.

*Texture-based methods* use the grain's surface texture. Fernandez-Delgado et al. [10] classified 5 pollen types using measurements of gray-level co-occurrence matrix, neighborhood gray-level dependence statistics, entropy, and the mean. DaSilva et al. [11] transformed pollen images using wavelet coefficients representing the spatial frequency, and then calculated gray-level co-occurrence matrix to classify 7 pollen species.

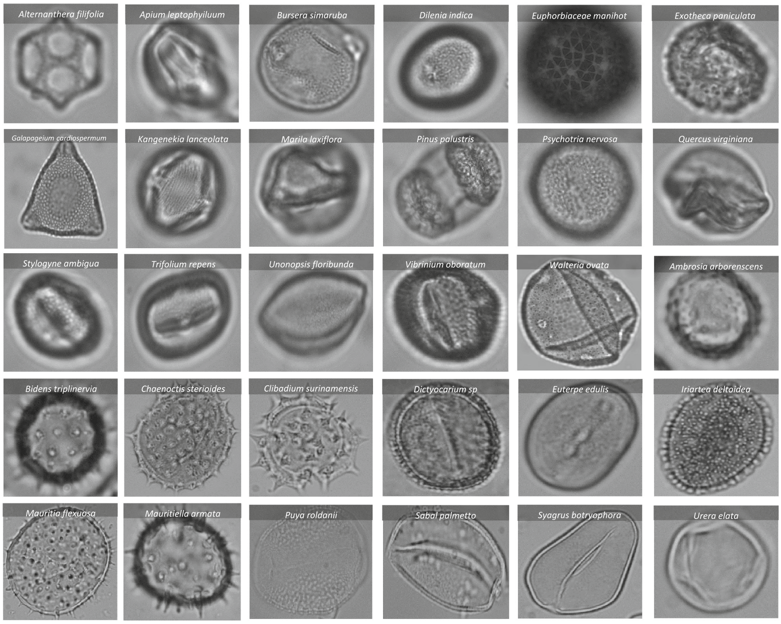
*Hybrid methods* combine multiple characteristics. Ticay-Rivas et al. [12] classified 17 plant species based on geometrical features (i.e., area, convex area, and perimeter), Fourier descriptors, and color features. A multi-layer neural network was used as a classifier. Chica [13] also combined textures and morphological characteristics to detect 5 classes of bee pollen. The features included shape (i.e., area, perimeter, diameter) and texture (i.e., mean, standard deviation, the entropy of the gray-level histogram).

An alternative approach to using pre-designed features is to try to learn optimal features from training data. This approach can be implemented using convolutional neural networks (CNN), a class of pattern-classification methods known as deep learning [14]. Deep learning has been shown to successfully solve challenging classification tasks [15]. In this paper, we present a pollen-classification method that uses deep learning to classify 30 pollen types of two image modalities: light-microscopy (LM) and scanning electron microscopy (SEM). Figure 1 shows example images from our dataset.

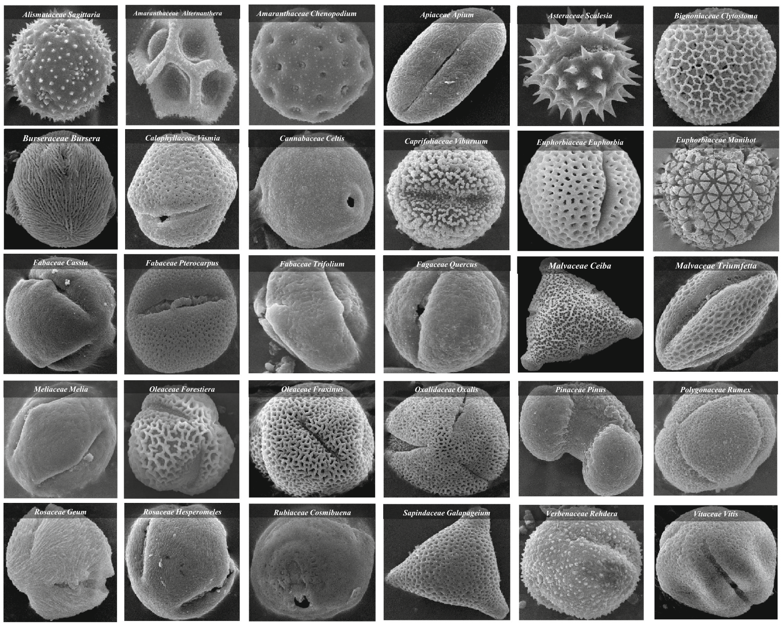
## 2 Method

Our CNN has seven learned layers. The first six layers are convolutional layers and the final layer is a fully connected layer. The convolutional layers share the same architecture, where each convolutional layer includes a filters unit, a rectified Units (ReLUs), a pooling unit, and a local normalization unit. Network configuration, such as network depth and filters' size, determines computational speed. Although increasing the depth and filters size of CNN improves the recognition rate, it consumes more CPU and memory.

In our work, image resolution, network depth (i.e., number of layers), filters' size for each individual layer, and the training window size (i.e., number of images




(a)




(b)

**Fig. 1.** One sample from each pollen type of our LM dataset. The dataset consists of some 1,000 images of 30 pollen types, provided by the our Paleoecology Laboratory. (a) LM dataset (b) SEM dataset.

used in the training process of each step to update networks parameters) were determined experimentally by maximizing the classification rate and using the available resources. For parameter initialization and learning rate, we followed [15]. The input of the first layer is $274 \times 274$ (i.e., the input image) with 50 filters of size $19 \times 19$. After the response is normalized and pooled, the second layer takes the output of the first layer and filters it with 75 filters of size $11 \times 11$. The number of filters and their size of the rest of layers are: 100, $8 \times 8$, 250, $5 \times 5$, 500, $4 \times 4$, 2000, $4 \times 4$, 30, $1 \times 1$. Stochastic gradient descent was used for the training process with window size of 25 images.

### 2.1 Training

The network has some 20 million parameters. Our dataset is small when compared to the number of learned parameters of the CNN. Training directly for all parameters using a small dataset may lead to over fitting. Therefore, a data-augmentation technique was used to artificially increase our dataset from 1,000 to 14,000 samples and 1,161 to 15,000 samples for LM and SEM respectively by applying different rotation transformations. Additionally, drop-out layers were attached to the last two layers by a 0.5 factor to reduce the over-fitting effect. Removing some units of a network during training prevented excessive parameter updating. This drop-out technique may help reduce over fitting [16,17]. Our results showed that data augmentation increased the classification rate by 24% and 27% for LM and SEM respectively. A zero-mean Gaussian distribution was used to initialize the weights in each layer. Biases were initialized with constant values of 1, and the learning rate equaled 0.001. We trained our network using the MatConvNet toolbox [18]. We trained our network for 60 epochs using our dataset, which took about three days to converge on a single machine with a core 7 processor and 16 G of memory.

### 2.2 Transfer Learning

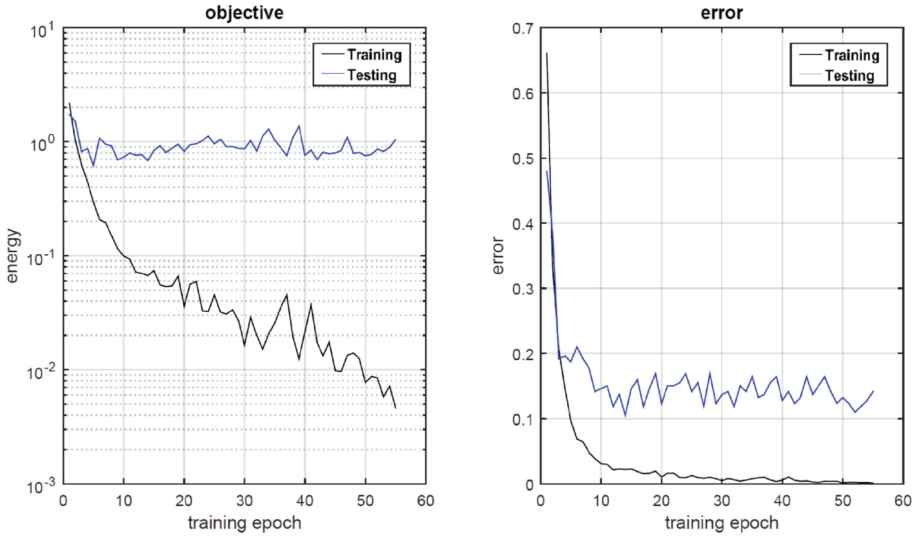
We improved classification performance by adopting the transfer-learning technique to leverage the learned knowledge from previous models [19]. A different architecture is used to apply the transfer learning where the input of the first layer is $294 \times 294$ (i.e., the input image) with 50 filters of size $19 \times 19$. The number of filters of the second layer is 48, of size $11 \times 11$. The number of filters and their size for the rest of layers are: 100, $5 \times 5$, 250, $3 \times 3$, 256, $3 \times 3$, 2048, $6 \times 6$, 30, $1 \times 1$. The first two layers were initialized from the previous model and the rest of layer were initialized from ImageNet model [20]. Basically, we selected the size of the filter of these layers to match the ImageNet model but we decreased the number of the filters because that model has a large number of parameters. We trained the CNN again to perform fine tuning to refine the network parameters. Additionally, we increased our dataset from 1,060 to 25,000 samples and 1,161 to 28,000 samples for LM and SEM respectively using data augmentation by applying different rotation and scale transformations.

## 3 Results

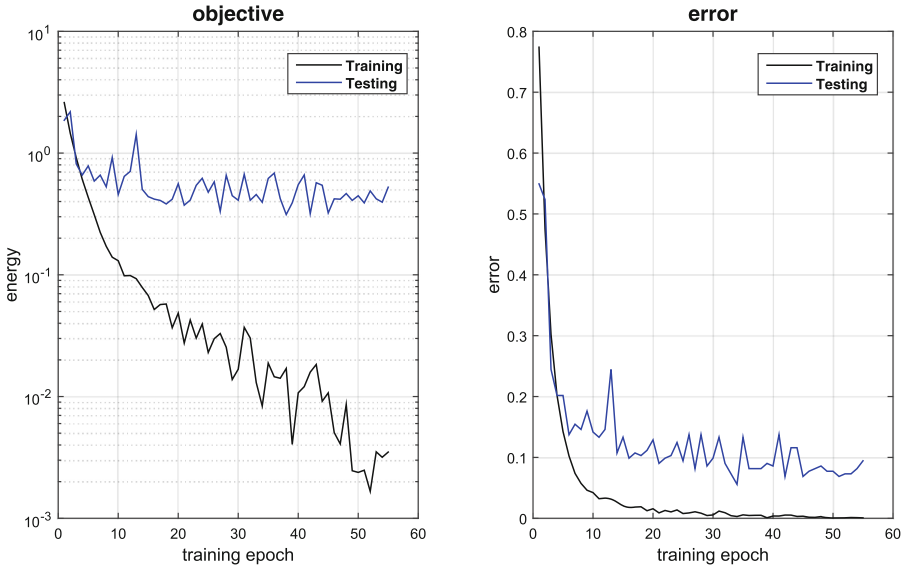
By using transfer learning, we increased the recognition rate to nearly 90%. Figure 2 shows the misclassification error and the objective energy of our network during training. The error rate and the objective energy were computed at each epoch and visualized to monitor the network's convergence. Figure 3 shows the learned filters of the first layer of our networks. We also compared the performance of our network with the traditional approaches that used the pre-designed features. Results of this comparison are shown in Table 1. These approaches are based on pre-processing the pollen grain images (i.e., enhancement and segmentation), pre-defined feature extraction, and classification. We used the following features: histogram features (i.e., mean and variance of histogram), gray level statistics (i.e., mean, variance and entropy), geometrical features (i.e., area, perimeter, compactness, roundness, and aspect ratio based on minor and major axises), fractal dimension, gray level co-occurrence matrix (GLCM), moments invariant, Gabor features, histograms of oriented gradient (HOG) descriptors, and local binary pattern histogram (LBP). After we performed features extraction, we trained a support vector machine classifier based on these features.

We also compared our method with two approaches in the literature that combined multiple features: Marcos's method [21] and Silva's work [11]. Marcos combined gray-level co-occurrence Matrix, Gabor features, local binary patterns, and discrete moments features. Silva decomposed the pollen grain into four layers using wavelet transform and then gray-level co-occurrence matrix was computed to create features vectors using statistical measurements. Table 1 shows the classification rates.

To prove statistically that our CNN is significantly better than traditional approaches, we computed the P-value. Based on Table 1, we compared our results with the best method that combined histogram, gray level statistics, fractal dimension, and LBP. The P-value was $2.56 \times 10^{-4}$ and $9.76 \times 10^{-6}$ for both LM and SEM respectively, which means null the hypothesis can be rejected. Additionally, we computed the average of precision, recall, sensitivity, specificity, and F score [22], which are shown in Tables 2 and 3.

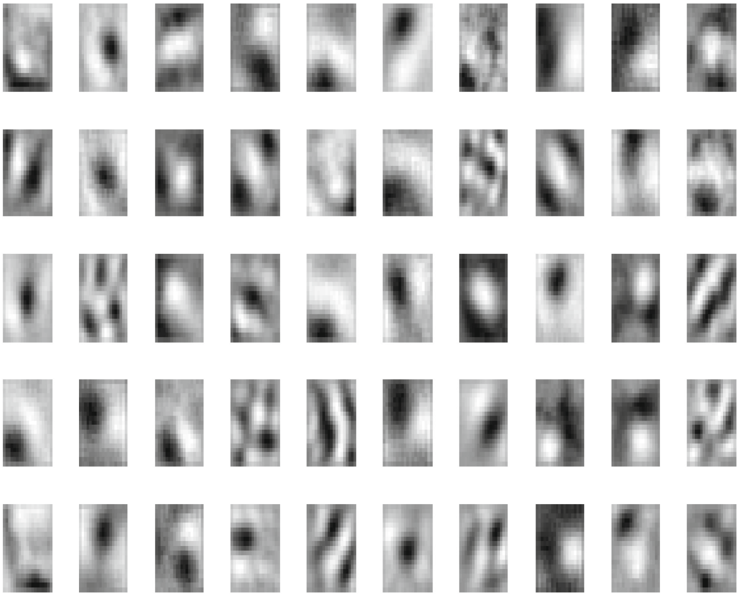



(a)

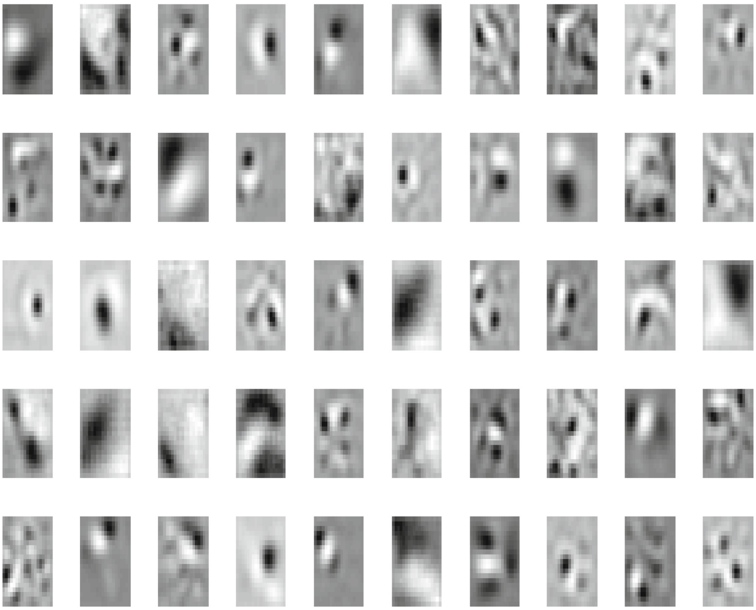



(b)

**Fig. 2.** Error and objective energy of the training process. At each iteration, feed forward technique is used to compute the objective function of the network, and the predictions of the training and testing samples to calculate the error rate. (a) LM dataset (b) SEM dataset.



(a)



(b)

**Fig. 3.** Learned filter of the first layer of CNNs. Basic features such as corners, edges, and blobs were learned. (a) LM dataset (b) SEM dataset.

**Table 1.** Classification rates

| Method | Classification rate of LM dataset | Classification rate of SEM datset |
|---|---|---|
| Histogram features, Gray level statistics | 70.97% | 61.20% |
| Geometrical features, fractal dimension | 71.97% | 60.59% |
| Gray level co-occurrence matrix | 51.34% | 48.24% |
| Moments invariants | 44.59% | 42.63% |
| Gabor features | 67.36% | 60.12% |
| HOG | 62.34% | 50.29% |
| LBP | 77.07% | 71.49% |
| Silva's Method | 67.36% | 59.55% |
| Marcos's Method | 78.92% | 74.96% |
| Histogram, Gray level statistics, fractal dimension, LBP | 80.19% | 78.11% |
| CNN | **84.47%** | **90.56%** |
| CNN (with transfer learning) | **89.95%** | **93.99%** |

**Table 2.** Evaluation measurements of LM dataset

| Method | Precision | Recall | Sensitivity | Specificity | F score |
|---|---|---|---|---|---|
| Features combination | 81.16% | 79.68% | 79.68% | 99.31% | 79.31% |
| CNN | **85.15%** | **84.28%** | **84.28%** | **99.48%** | **83.82%** |
| CNN (with transfer learning) | **92.04%** | **90.26%** | **90.26%** | **99.65%** | **89.13%** |

**Table 3.** Evaluation measurements of SEM dataset

| Method | Precision | Recall | sensitivity | specificity | F score |
|---|---|---|---|---|---|
| Features combination | 81.03% | 77.83% | 77.83% | 99.24% | 78.30% |
| CNN | **93.12%** | **90.45%** | **90.45%** | **99.70%** | **91.17%** |
| CNN (with transfer learning) | **95.00%** | **93.92%** | **93.92%** | **99.79%** | **94.05%** |

## 4 Conclusion and Future Work

In this paper, we proposed an approach to identify 30 types of pollen grain. The approach is implemented using a convolutional neural network. We trained a convolutional neural network to learn discriminating features such corners, blobs, and edges. The set of the learned features are used to classify the pollen grain images. Data augmentation and a drop-out techniques were used to reduce over fitting. Moreover, we adopted a transfer-learning technique to leverage learned features to improve classification rates. Experimental results showed that extracting features automatically using CNN has superior performance over the traditional techniques. Even though our approach offers promising classification rate, the training time of the convolutional neural networks becomes an issue especially when it runs on standard PCs. Increased processing speed can be achieved using parallel processing and GPU architectures.

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