Identification of *Onopordum* pollen using the extreme learning machine, a type of artificial neural network

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Pollen grains are complex three-dimensional structures, and are identified using specific distinctive morphological characteristics. An efficient automatic system for the accurate and rapid identification of pollen grains would significantly enhance the consistency, objectivity, speed and perhaps accuracy of pollen analysis. This study describes the development and testing of an expert system for the identification of pollen grains based on their respective morphologies. The extreme learning machine (ELM) is a type of artificial neural network, and has been used for automatic pollen identification. To test the equipment and the method, pollen grains from ten species of *Onopordum* (a thistle genus) from Turkey were used. In total, 30 different images were acquired for each of the ten species studied. The images were then used to 11 measure morphological parameters; these were the colpus length, the colpus width, the equatorial axis (E), the polar axis (P), the P/E ratio, the columellae length, the echinae length, and the thicknesses of the exine, intine, nexine and tectum. Pollen recognition was performed using the ELM for the 50–50%, 70–30% and 80–20% training-test partitions of the overall dataset. The classification accuracies of these three training-test partitions of were 84.67%, 91.11% and 95.00% respectively. Therefore, the ELM exhibited a very high success rate for identifying the pollen types considered here. The use of computer-based

systems for pollen recognition has great potential in all areas of palynology for the accurate and rapid accumulation of data.

Keywords: artificial neural network; automatic identification; expert system; extreme learning machine; *Onopordum*; pollen; Turkey

1. Introduction and background

Pollen grains are produced by seed plants to disseminate their haploid male genetic material. Each pollen grain contains a generative cell (the male gametes) and a vegetative cell or cells, surrounded by a cellulose cell wall and a tough outer wall made of the resistant polysaccharide sporopollenin (Edlund et al. 2004). The morphology of pollen grains is extremely characteristic and pollen can, by itself, be used as a proxy for the respective parent plant. These features are used to identify taxa and hence are useful for establishing phylogenies (e.g. Clark et al. 1980). Pollen analysis is an extremely important discipline and its practitioners, termed palynologists, study diverse topics such as the indications and timings of anthropological activity, limnology, rapid climatic/ecological change and vegetational history (e.g. Moore et al. 1991). Pollen morphology is an essential part of general plant morphology, and hence plays a critical role in research into taxonomy and evolution. Most morphological features of pollen allow identification only to the generic level. This is because the majority of morphological characters are very similar within a genus, and it is normally difficult to subdivide genera using conventional light microscopical techniques.

The traditional method of pollen identification using a transmitted light microscope requires an experienced palynologist, and can be somewhat time-consuming. Hence an automated system for the location of pollen grains on microscope slides and their identification would be hugely beneficial in the interests of economics and efficiency in all types of pollen analysis. Several attempts at developing reliable expert systems have been made, and these are reviewed in section 2 below.

In this study, an automatic pollen recognition system using a neural network is trialled. A learning algorithm termed the extreme learning machine (ELM) was used to perform the analyses on ten species of a thistle genus *Onopordum* (Family Asteraceae, Subfamily Carduoideae, Tribe Cynareae). The ELM is a single hidden layer feed-forward neural network (SLFN), and is a specialised artificial neural network (ANN) model. With the ELM, the weightings belonging to neurons at the input layer, and the bias values belonging to neurons in the hidden and input layers are all randomly-generated. By contrast, the outputs from the hidden layer are computed analytically (Huang & Siew 2005, Li et al. 2005, Huang et al. 2006a,b, Rong et al. 2008, Suresh et al. 2010). The most significant feature of the ELM model is that the learning process is very efficient. It can learn thousands of times faster than conventional learning algorithms for feed-forward neural networks. The learning speed of other feed-forward neural networks is typically relatively slow, largely due to the slow gradient-based learning algorithms used in the training procedure (Huang et al. 2006b).

Automated recognition tools such as the ELM, and the necessary computer hardware, are presently at a stage where these methods can potentially be routinely applied to the analysis of pollen assemblages. In theory, automated pollen identification and classification should remove analytical subjectivity and inconsistencies between operators. Furthermore, analyses should be completed more rapidly than with an actual palynologist, hence making savings in terms of both time and labour. Automatic systems can be rapidly programmed to analyse different pollen assemblages in terms of geographical locus, geological age and taxonomic focus (families, genera, species etc.). This makes them potentially more adaptable than any single palynologist.

2. Previous research on the automated identification of pollen

Several studies have attempted the digital identification of pollen using artificial intelligent systems, and selected relevant studies are briefly reviewed here. Early studies include Langford et al. (1990) and Vezey & Skvarla (1990), who undertook research into pollen recognition using the scanning electron microscope (SEM), and achieved promising results.

Both these studies developed computer systems which were designed to classify pollen grains based on their surface texture. However SEM analysis is relatively expensive and rather slow, and hence is unsuitable for applications which require data and interpretations in a short timeframe. Benyon et al. (1999) used image analysis to attempt to differentiate eleven allergenic fungal spore genera. This study was based on 24 morphological features extracted from digitised images. These authors found that using linear and quadratic discriminant analysis allowed the recognition of both genera and species with a high level of accuracy. France et al. (2000) developed a new approach to this problem based on improving the quality of the image processing with a traditional optical microscope. These authors were able to differentiate between pollen grains and palynodebris, and to classify three different pollen types correctly. Jones (2000) and Ronneberger (2000) investigated pollen recognition using two-dimensional statistical classification and three-dimensional greyscale invariants with confocal microscopy respectively. Boucher et al. (2002) developed a semi-automatic system for pollen recognition. Digitised three-dimensional photographs of Cupressaceae (cypress), *Olea* (olive), Poaceae (grasses) and Urticaceae (nettle) pollen were image-processed in two and three dimensions, and around 77% of the pollen grains were identified by this system, which worked especially well for pollen from the families Poaceae and Urticaceae. Rodriguez-Damian et al. (2006) developed an automatic system for the identification of species of pollen from the Family Urticaceae using a combination of shape and textural analysis. This system achieved 89% of reliable pollen identifications.

Li & Flenley (1999) successfully used texture analysis to identify pollen using transmitted light microscope images with neural network analysis, which is a statistical classifier. Ranzato et al. (2007) developed a microscopic image analysis system. This four-stage process was first used to classify 12 microscopic particle types found in human urine, where it achieved a 93.2% success rate. It was then trained and tested on a set of images of airborne pollen grains, where it generated 83% of positive identifications. Allen et al. (2008) and Holt et al. (2011) developed an automated system that locates, photographs, identifies and counts pollen on a conventional microscope slide. The images in Holt et al. (2011) were analysed with an array of mathematically-defined parameters defined by Zhang et al. (2004), and the feature sets obtained were classified using similar sets from known pollen types. The images produced were then checked by a palynologist. Holt et al. (2011) produced pollen counts which only vary within 1–4% of the results produced conventionally by a palynologist.

An innovative methodology to discriminate three species of pollen from the Family Urticaceae (*Parietaria judaica, Urtica membranacea* and *Urtica urens*) using computer techniques for the definition of digital shape parameters to represent a pollen grain was developed by de Sá-Otero et al. (2004). This system uses area, diameter, mean distance to centroid and roundness, and achieved an at least 86% success rate.

Ticay-Rivas et al. (2011) used Fourier descriptors of the morphological details (geometrical parameters) of 17 honey plant pollen species using discrete cosine transform, together with colour information in order to effect automatic identifications. These authors used a multi-layer neural network, and their method acheived a mean of 96.49% ±1.15 for successful identifications. Recently Kaya et al. (2013) described an expert computer system using a rough set approach for the automatic classification of 20 types of *Onopordum* pollen. Each pollen grain was comprehensively photographed, with 30 different images captured. Key morphological parameters such as the colpus length, the P/E ratio and the echinae length were measured. The dataset of Kaya et al. (2013) comprised 600 pollen samples; 440 samples were used for training the expert system, and the remaining 160 were used for testing using the rough set approach. This method correctly identified 145 of the 160 pollen grains tested, a success rate of over 90%.

3. The plant family Asteraceae and the genus *Onopordum*

This study is an attempt to distinguish species of *Onopordum* L., a genus of thistles within the Family Asteraceae using automatic pollen identification. The Asteraceae are commonly referred to as the aster or daisy family. It is the largest family of flowering plants, and was formerly known as the Compositae (Wagenitz 1976, Bremer 1994, Funk et al. 2005, Panero & Funk 2008). This major plant family is extremely geographically widespread, and is represented by over 1600 genera and approximately 23000 species of herbs, shrubs and trees throughout the world (Kubitzki 2007). Of these taxa, 143 genera and approximately 1484 species are present in Turkey (Davis 1975, Özhatay et al. 2009). Pollen grains of the Asteraceae are relatively similar in overall morphology throughout the family. The genus

Onopordum L. is a thistle genus within the Subfamily Carduoideae of the Asteraceae, and includes around 60 species which inhabit north Africa, west and central Asia, the Canary Islands and Europe (Kubitzki 2007). In Turkey, *Onopordum* comprises 19 species, and 2 subspecies (Danin 1975, Davis et al. 1988, Özhatay et al. 1994, Güner et al. 2000). *Onopordum* pollen is oblate-spheroidal in shape and the grains occur as monads (Plate 1). Most of the measurable morphological characters are similar in *Onopordum,* and it is difficult to consistently distinguish the species from one another using normal microscopy techniques.

4. Material studied

The pollen grains of the constituent genera within the Family Asteraceae are morphologically very similar, hence they are eminently suitable for the testing of digital identification methods. Material used in this study was 10 species of *Onopordum* which were collected from wild populations in Turkey. Plant specimens and permanent pollen slides have been deposited in the herbarium and the pollen reference collection respectively of the Department of Biology, Faculty of Science, Yüzüncü Yıl University, 65080 Van, Turkey.

Pollen was prepared using the technique of Wodehouse (1959); the mounting medium used was glycerin-jelly mixed with 1% Safranin. The slides were studied using an Olympus CX31 light microscope with a 100x oil immersion objective. Measurements were based on 30 images of each of the specimens studied, which were manipulated manually where necessary. The specimens were photographed; the resolution of the digital images was 710×720 pixels. All measurements of the pollen grains were made using Olympus Stream micro-imaging software, a computer program; that automatically calculates the distance from any two points.

The polar axis (P) and the equatorial axis (E) were measured in all the specimens, and the P/E ratio calculated. It should be noted that the term equatorial axis is often inappropriately used as a synonym for the equatorial diameter (Punt et al. 2007). Additionally, the colpus length and width, the lengths of the columellae and echinae, and the thicknesses of the exine, intine, nexine and tectum were also measured (Plate 1). These 11 parameters are all used for the identification of pollen grains in the Family Asteraceae, and were deemed to be appropriate for use in digital identification. The pollen terminology of Faegri et al. (1989) and Punt et al. (2007) was used.

5. The methodology of the extreme learning machine (ELM)

Feed-forward neural networks (FFNNs) are ideal classifiers for nonlinear mapping investigations that utilise a gradient descent approach for weights and bias optimisation. The important factors that influence the performance of a traditional FFNN algorithm include three important features. The first are small values for the learning parameters which cause the learning algorithm to converge slowly, whereas higher values lead to instability and divergence to a local minimum. The second is that conventional neural networks may be over-trained using back propagation and normally generate inferior generalisation performance. Finally, gradient descent-based learning is an extremely time consuming process for most applications. To overcome these problems, Huang & Siew (2005), Li et al. (2005) and Huang et al. (2006a,b) proposed a learning algorithm called the extreme learning machine (ELM) for single-hidden layer feed-forward networks (SLFNs). The ELM is a SLFN model in which the input weights are random, and the output weights are obtained analytically (Liang et al. 2006, Yuan et al. 2011). The SLFN structure is illustrated in Figure 1. The authors believe that the ELM should be tested in the automatic identification of pollen grains. This method is potentially superior to other methods such as decision tree and linear discriminant analysis. Furthermore, the ELM offers faster learning times than other neural networks. Specifically, the five most important features of the ELM are listed below:

- The ELM is extremely fast
- The ELM has better generalisation performance
- The ELM tends to reach solutions in a straightforward manner without extraneous issues such as local minima, learning rate, momentum rate and over-fitting, which are all encountered in traditional gradient-based learning algorithms

- The ELM algorithm can be used to train SLFNs, with many non-differentiable activation functions
- The ELM randomly chooses and fixes the weights between the input and hidden neurons based on continuous probability density functions, which is a uniform distribution function in the range -1 to +1. Then it calculates analytically the weights between the hidden neurons and the output neurons of the SLFN.

According to Figure 1, on determining that $X = (X_1, X_2, X_3.....X_N)$ is input and $Y = (Y_1, Y_2, Y_3.....Y_N)$ is output, the mathematical model with *M* hidden neurons is defined as in Suresh et al. (2010):

$$\sum_{i=1}^{M} \beta_i g(W_i X_k + b_i) = O_k \quad , \quad k = 1,2,3.......N \qquad (1)$$

Where $W_i = (W_{i1}, W_{i2}, W_{i3}.....W_{in})$ and $\beta_i = (\beta_{i1}, \beta_{i2}, \beta_{i3}.....\beta_{im})$ are the input and output weights; b_i is the bias of the hidden neuron and O_k is the output of the network. $g(.)$ denotes the activation function (Rong et al., 2008).

In a network of *N* training samples, the aim is zero error: $\sum_{k=1}^{N}(O_k - Y_k) = 0$ or with minimum error: $\sum_{k=1}^{N}(o_k - Y_k)^2$. Therefore, Equation 1 can be shown as below (see Huang et al. 2006b):

$$\sum_{i=1}^{M} \beta_i g(W_i X_k + b_i) = Y_k \quad , \quad k = 1,2,3.......N \qquad (2)$$

This is because, in the equation above, $g(W_i X_k + b_i)$ denotes the output matrix in the hidden layer; Equation 2 is therefore as in Huang et al. (2006b):

$$H\beta = Y \qquad (3)$$

This is where:

$$H(W_1,........W_M;b_1,........b_M;X_1,.......X_N) = \begin{bmatrix} g(W_1X_1+b_1)..... & g(W_MX_M+b_M \\ . & . \\ . & . \\ g(W_1X_N+b_1)...... & g(W_MX_N+b_M) \end{bmatrix} \quad (4)$$

And

$$\beta = \begin{bmatrix} \beta_1^T \\ . \\ . \\ \beta_M^T \end{bmatrix}_{Mxm} \quad and \quad Y = \begin{bmatrix} Y_1^T \\ . \\ . \\ Y_N^T \end{bmatrix}_{Nxm} \quad (5)$$

This is where *H* is the hidden layer output matrix. Training of a network in a traditional feed-forward ANN means seeking a solution for the least squares in a linear equation of $H\beta = Y$ in the ELM (Suresh et al., 2010).

$\hat{\beta} = H^{+}Y$ is the smallest norm least-squares of $H\beta = Y$. In addition, H^{+} denotes the Moore-Penrose generalised inverse of the hidden-layer output matrix *H*. The norm of $\hat{\beta}$ is the smallest solution among all the least-squares solutions of the $H\beta = Y$ equation (Huang et al., 2006b). Therefore the ELM can minimise the training error.

The ELM algorithm can be summarised in three stages as follows:

1. The $W_i = (W_{i1}, W_{i2}, W_{i3}.....W_{in})$ input weights and hidden layer b_i bias values are produced randomly
2. The H hidden layer output is computed
3. The $\hat{\beta}$ output weights are computed according to $\hat{\beta} = H^{+}Y$. Y is a decision feature.

In this study, an automatic model based on the ELM method was used for the identification of *Onopordum* pollen. A block diagram describing this model is illustrated in Figure 2. The process comprises five blocks, which are summarised below:

Block 1: Obtaining 30 images in different orientations for each of the 10 species studied

Block 2: Obtaining the key 11 morphometric measurements for each pollen image

Block 3: Division of the pollen data sets into training-test partitions at different rates, i.e. 50–50%, 70–30% and 80–20%

Block 4: Classification of the training-test partitions through the ELM

Block 5: Presentation of the classification results, i.e. the decision stage

6. Results

6.1. Parameter selection

In this study, morphological features that were measured from pollen images were processed by the ELM to effect pollen identification. The 11 parameters used in the ELM network are listed in Table 1. The performance of the ELM network depends on the number of neurons in the hidden layer and the activation function that was used. Consequently, the appropriateness of the parameters in Table 1 were decided as a result of trials. Hence, activation functions such as sigmoid, tangent sigmoid, sine and radial basis were used for the training and testing of the network. The numbers of neurons in the hidden layer between 10 and 100 were finalised by being tested, and this figure was iterated by increasing it one-by-one. The most appropriate activation function and neuron number were finalised only after exhaustive training and testing of the network. For the identification of *Onopordum* pollen, the most appropriate activation function was tangent-sigmoid.

6.2. Results derived from the experiments using the extreme learning machine

The pollen identification experiments were conducted by performing training test sets at the rates of 50–50%, 70–30% and 80–20% through the ELM with the overall pollen dataset. The classification accuracies of these training-test partitions were 84.67%, 91.11% and 95.00%, respectively (Table 2). These accuracies demonstrate that the ELM is consistently very effective. It was found that the ELM has sufficient identification resolution to discriminate *Onopordum* pollen at the species level. In Figures 2, 3, 4 and 5, the ELM performance values related to changes in neuron number used in the hidden layer are illustrated for the training-testing rates of 50–50%, 70–30% and 80–20%, respectively.

Different machine learning methods were also used here for automatic pollen identification using the same dataset and images. The accuracies of an artificial neural network (ANN), a support vector machine (SVM; see Chang & Lin 2001), the J48 decision tree method (Quinlan 1993), PART (Eibe & Witten 1998), a logistic regression and the ELM machine learning methods for different training-test partitions were given in Table 2. The ELM gave the highest accuracy for *Onopordum* pollen identification (Table 2).

7. Conclusions

Specific features of pollen can help to identify grains to family or genus level using automated diagnostic systems. These methods potentially allow the accurate and rapid identification of pollen grains, and will be useful in all areas of palynology. In this study, pattern recognition methods were used to determine the pollen type.

Morphological characteristics are normally used for identification in plant systematics at all levels from classes to subspecies/varieties. However, at the lower levels, other techniques may be useful to complement the morphological parameters. Pollen morphologies are relatively diverse, and the classification at the family and genus level should be relatively straightforward using traditional microscopy. Computer systems, however, have great potential for performing automatic identifications at the species level and below, due largely to apparent morphological similarities. Hence, the development of automated digital identification systems is predicted to be a significant growth area in the future. The positive results obtained herein from the large and diverse Family Asteraceae, should facilitate more studies on the digital identification of the pollen of other plant families. This field is a rapidly-developing one, and much more experimentation is needed using different characters and criteria in order to improve taxonomic accuracies.

In this study, a highly successful approach to automatic pollen recognition and classification using the ELM is demonstrated. The classification process was accomplished using 11 morphological characters for 10 different types of pollen. The identification accuracies of the training-test sections of 50–50%, 70–30% and 80–20% were 84.67%, 91.11% and 95.00% respectively (Table 2). The results herein using the ELM compare very well with other expert systems for identifying pollen grains. The identification rate of automatic diagnostic systems will potentially be higher than results obtained manually because of the strict morphometric approach of the former.

Acknowledgements

The authors wish to thank Dr Katherine Holt of Massey University, New Zealand and an anonymous reviewer for their constructive and perceptive critiques of the original manuscript. James B. Riding publishes with the approval of the Executive Director, British Geological Survey (NERC).

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Morphological feature/parameter	**Definition**
P	The length of the polar axis
E	The length of the equatorial axis
P/E	The P/E ratio
Colpus (L)	The length of the colpus
Colpus (W)	The width of the colpus
Exine	The thickness of the exine
Intine	The thickness of the intine
Nexine	The thickness of the nexine
Tectine	The thickness of the tectine
Echinae	The length of the echinae
Columellae	The length of the columellae

Table 1. The 11 training parameters (morphological features) used with the extreme learning machine (ELM) network in this study.

Name of automatic system	50–50% training-test (%)	70–30% training-test (%)	80–20% training-test (%)
Artificial Neural Network	80.00	80.66	84.44
Extreme Learning Machine	**84.67**	**91.11**	**95.00**
J48 Decision Tree	72.00	81.11	85.00
Logistic Regression	68.88	76.00	76.66
PART	75.33	75.55	83.33
Support Vector Machine	78.66	86.66	88.33

Table 2. The performance values of automatic pollen identifications using six different automatic systems. The extreme learning machine (ELM) results are in bold font.

Display material captions:

Figure 1. The structure of a single-hidden layer feed-forward (SLFN) artificial neural network.

Figure 2. A block diagram illustrating the method for pollen identification used herein.

Figure 3. Training and test efficiencies for the 50–50% training-test partition.

Figure 4. Training and test efficiencies for the 70–30% training-test partition.

Figure 5. Training and test efficiencies for the 80–20% training-test partition.

Plate 1. Two images of *Onopordum* pollen illustrating the various morphological measurements made in this study. 1 – grain in polar view. 2 – grain in equatorial/lateral view.