Automatic Classification of Desmids Using Handcrafted Texture Descriptors

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Abstract. Algae plays a vital role in aquatic ecosystem and serves as indicator for various issues related to water quality. In addition to these algae have various application in day to day life such as nutrition, fish feed, agriculture fertilizer, medicine, space research etc. More than 5000 species are discovered by the scientist and still research is going on. Manual classification of microscopic algae is very tedious task as it involves burden of taxonomic investigation whereas machine learning based algorithms play vital role and requires only one-time training. In this paper, we presented a method for automatic classification of desmids using handcrafted descriptors. Our algorithm involves three common steps of Patter Recognition algorithm such as pre-processing, feature computation and classification. We have applied image resize and colour to gray level conversion operation during processing. Histogram of Oriented Gradients, Local Binary Pattern and Local Phase Quantization are used for texture description. Nearest Neighbour Classifier, Linear Discriminant Analysis and Support Vector Machines were tested for classification of desmids. We have achieved encouraging results during our experiments on dataset of five classes of desmids.

Keywords: Unicellular Algae · Computer Vision · Texture Descriptors · Support Vector Machine · Linear Discriminant analysis

1 Introduction

Freshwater wetlands are significant ecosystems, and the benthic, attached microbial communities that live in them, including desmids, are vital habitats that help with primary productivity, nutrient cycling, and substrate stabilisation [1]. Desmids are unicellular biomass algae found in freshwater ecosystem.

As biologists, tiny desmids have piqued their curiosity. It is a complex group of microorganisms found in aquatic environments all over the world. Desmids come in a variety of forms and have applications in a variety of fields. Scientists are attempting to discover how to harness these microscopic creatures for the benefit of humanity's wellbeing, such as an alternative fuel, food, and so on.

Desmids identification has traditionally been performed manually, which is a tough and time-consuming task. And some species' likeness creates human error because they

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are unable to judge it effectively. On the other hand, computer vision-based systems provide efficient and dependable outcomes, as well as a guarantee of a result. As a result, we proposed an automated technique for classifying desmids from microscopic pictures. In this paper we proposed a system based on popular handcrafted descriptors for classification desmids automatically using computer vision techniques.

2 Literature Review

Classification of microscopic algae is problem of active research since last decade, there few algorithms are presented by researchers based on locally available resources and problems. In [9] presented a method for commonly found algae classification, to do this they applied segmentation using edge detection followed by morphological operations. Various features were computed such Fourier descriptors, Moment invariants, shape features, textures features based on GLCM. SMO classifier was sued for algae classification. Based on contour analysis and scale space features, Imaging cytometry based study was presented in [10], various shape descriptors, texture descriptors and binary shape measures were used with Random Forest Classifier and CNN.

The authors of [11] established a unified paradigm for diatom identification. They also compared their strategy to state-of-the-art descriptors like the Gabor filter and moments, and found that it performed better. On a huge dataset of diatom photos, handcrafted features are examined [12]. The authors used local binary patterns and log Gabor filters to classify diatoms using several classifiers such as SVM, K-means, Decision trees, Boosting, and Bagging with 10-fold cross validation and reached a result of 98.10 percent. [13] presents convolution neural networks-based deep learning for diatom classification, which demonstrated promising accuracy with a huge dataset of diatoms belonging to 80 categories. Using microscopic algae photos from the Scenedesmus group, [14] authors constructed a system based on statistical features and texture descriptors, achieving a result of 98.63 percent with SVM and 97 percent using artificial neural networks. Authors presented a technique for recognizing and classifying freshwater algae in [15]. To begin, each segmented item is segmented, and binary shape descriptors are extracted from each segmented object. Fourier spectrum descriptors were extracted, and PCA was used to pick features. MLP and ANN were used to classify the data.

Recently authors in [16] evaluated the performance of AlexNet for classification Scenedesmus algae for application to biomonitoring. They have trained the AlexNet on their dataset from scratch with existing weights form ImageNet and achieved the performance with accuracy of 96%.

From the above aforementioned paragraphs, it can be understood that automatic classification algae still have a room for research as studies are carried out based on locally available data and issues. Best of our knowledge this is first study presented for automated desmids classification using image processing machine learning.

3 Proposed Method

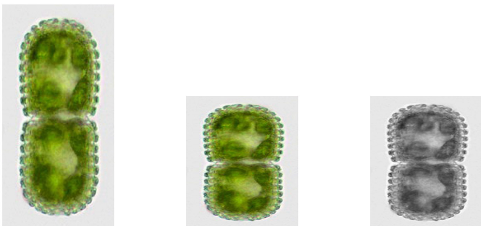
A. Pre-processing

In our method we have applied two pre-processing steps, as these steps are important to prepare the image for accurate feature description and most of the times these steps are depends on application. We aimed for desmids classification using texture descriptors and hence we have applied the two operations as pre-processing 1) image resize to size 164 × 164 this is fixed empirically and 2) RGB to gray conversion as gray level conversion allows to reduce the size of memory and texture description become easy with gray values for the feature extraction techniques considered (Fig. 1).

B. Feature Extraction

Local Binary Patterns: Local binary pattern [6] is the texture descriptor which takes a fixed threshold for binary image and gives 8-bit code in terms of binary value; after that, the code is converted into decimal value then this decimal number value of the image is drawn in a histogram and used as features, to make this rotation invariant more compact these descriptor values are classified again into two categories having transition and no transition in binary values and hence we get a total of 59 features which are called as Uniform Local Binary Patterns [5] (Fig. 2).

Histogram of Oriented Gradients: Histogram of Oriented Gradient is well known shape descriptors used for detection human poses [8] based on the principles occurrence of gradient orientation in localized portions of the image. First, the image is divided into small windows are known as cells and these cells are in different sizes in our case we have cell size of 32 × 32 which fixed empirically. And so on it may differ for different applications. Then these cells are connected to form a block from each block values are considered formed a histogram representation (Fig. 3).



(a) (b) (c)

Fig. 1. Original Image of Desmids and Resized and Grayscale Image

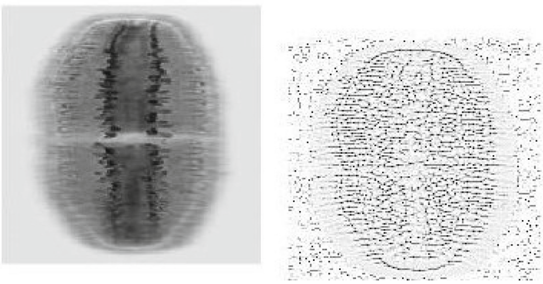


Fig. 2. a) Grayscale Image of Desmid b) LBP Texture Image of Desmid

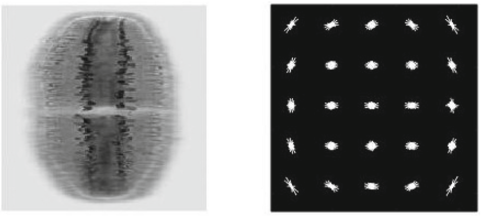


Fig. 3. a) Grayscale Image of Desmid b) HOG Computation

Local Phase Quantization: Local phase quantization [7] is one of the Fourier phase information of blur insensitive property or it is a texture descriptor, which extracts the local information from the images by computing STFT over a rectangular neighbourhood Nx of size M by M. which is nothing but calculating the four frequency coefficients at the four different points on a pixel. And we get four real and four imaginary values in two-bit code and then this two-bit code is converted into 8- bit code. And a histogram of 8-bit code is drawn, pixel position is used as features and here we get 256 features for one image (Fig. 4).

C. Classification

Nearest Neighbour Classifier: The most common and traditional method for classification, the Nearest Neighbour Classifier is utilized. It is a learning algorithm that is supervised in nature. An appropriate distance measure can be used to find the nearest neighbour. We employ Euclidean distance as a distance measure in this study to locate the closest neighbour. If P represents the training data and Q represents the testing sample, then the Euclidean distance between P and Q is:

$$D(P, Q) = \sqrt{\Sigma_{i=1}^{n}(P_i - Q_i)^2} \quad (1)$$

Support Vector Machine: Vapnik [18] developed the SVM classifier. Among the others, SVM is known as the most sophisticated classifier. SVM maps m-dimensional input space X to l-dimensional feature space z. The optimal separating hyper-plane is used to solve the z quadratic programming problem of separating two classes. Kernel strategies can be used to expand the basic SVM [2]. In our experiment, we used SVM with the

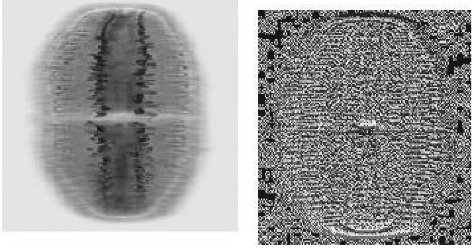


Fig. 4. a) Grayscale Image of Desmid b) LPQ Texture Image of Desmid

RBF kernel function, which gives us the following decision function:

$$D(X) = \sum\nolimits_{i \in S}^{\infty} \alpha_{iy_i} \exp\left(-\gamma||xi - x||^2\right) + b \tag{2}$$

In this case, support vectors are centres of RBF, more details are given in [2, 3].

Linear Discriminant Analysis: Linear discriminant analysis is popular classifier due it simplicity, ease of implementation and generalization ability. Higher level of class discrimination is archived in LDA by maximizing the ratio of between class to within class variance [17]. Here we used the LDA to classify the desmids. The classification function for dataset X of desmids and classes C in our case C = 5 given as:

$$g(X) = WTX \tag{3}$$

where W represents the linear projections.

The between class scatter matrix Sb given as

$$Sb = \sum_{i=1}^{c} ni(m_i - m)(mi - m)^T \tag{4}$$

where mi represents the mean of ith class and m is the overall mean.ni are the number of samples in ith class.

The within class scatter matrix is Sw is given as

$$Sw = \sum\nolimits_{i=1}^{c} \sum\nolimits_{x \in X} (X - mi)(X - mi)^T. \tag{5}$$

Now, given the Quadratic distance d of g(X) and centers Vi = WT mi compared in LDA space and new sample classified to class label $\omega \in C$, accordingly:

$$\omega = \arg \min_{1<=i<=c} d(g(X), Vi) \tag{6}$$

D. Dataset and Evaluation Protocol

Dataset: We have used five types of desmids genus with total 88 microscopic images with varied angels, sizes and shapes for automatic classification desmids namely.

1. Closteriaceae (27),
2. Desmidiaceae (23),
3. Gonatozygon (13),
4. Mesotaeniaceae (33),
5. Peniaceae (19)

This is one of the most versatile data of microscopic image is considered for the experiments and evaluation of our method from [4]. The samples of microscopic images are shown in Fig. 5.

Evaluation Protocol

Most popular method is used for evaluation of proposed approach, named as k- fold

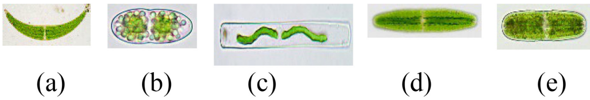


Fig. 5. Samples of microscopic images of desmids from our dataset a) Closteriaceae b) Desmidiaceae c) Gonatozygon d) Mesotaeniaceae e) Peniaceae

cross validation. The dataset is randomly partitioned in to k sub folds. Each time one fold is considering for testing and rest for training. Process is repeated until each fold has got opportunity to serve for training and testing. In our experiment we considered k = 10. We have defined accuracy as following:

$$\boldsymbol{Accuracy} = \frac{\textbf{\textit{Correctly Classified desmids in class}}}{\textbf{\textit{Total Desmids in class}}} \tag{7}$$

4 Results and Discussion

In this work, our aim is to automatic identify the genus of desmids with the handcrafted descriptors due to their power of texture description. To evaluate our method, we have performed exhaustive experiments with three well known feature extraction methods namely LBP, HOG and LPQ by combining with three popular and efficient classifiers namely NN Classifier, SVM classifier and LDA Classifier. Due to the limited and imbalanced dataset, we have applied the cross validation and error average was computed.

In Table 1 we have details the accuracies given by various classifiers and feature extraction techniques. It can be noted that HoG has given superior performance as compared to LBP and LPQ whereas among the classifiers SVM has given the highest accuracy i.e. 86.1% with HOG, 81.2% with LPQ and 78.3% with LBP. The performance of Nearest Neighbor classifier was also good follwed by SVM with accuracies of 81.7%, 84.3% and 76.1% with LBP, HOG and LPQ respectively. LDA has performed average as compared to NN and SVM and given accuracy of 67.8%, 84.3% and 69.4% respectively with LBP, HOG and LPQ.

For deeper understanding we have also shown the confusion matrix for highest and lowest accuracies obtained during desmids recognition in Figs. 6 and 7 respectively.

Table 1. Desmids Recogntion Accuracy given by Local Binary Patterns

Feature Extraction /Classifier	Nearest Neighbour Classifier	Support Vector Machine	Linear Discriminant Analysis
Local Binary Patterns	81.7%	78.3%	67.8%
Histogram of Oriented Gradients	84.3%	86.1%	84.3%
Local Phase Quantization	76.1%	81.2%	69.4%

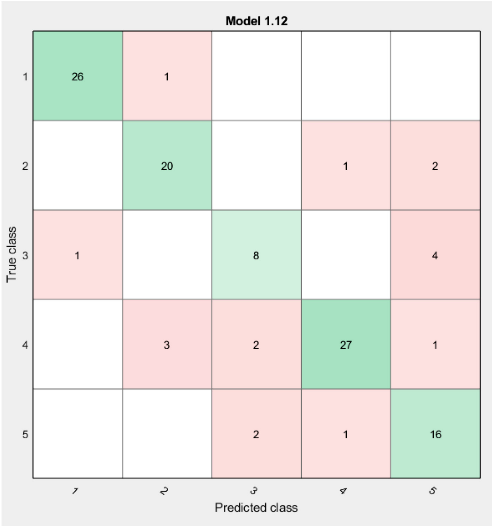


Fig. 6. Confusion Matrix given HOG with SVM for Highest Recognition Accuracy for Desmids

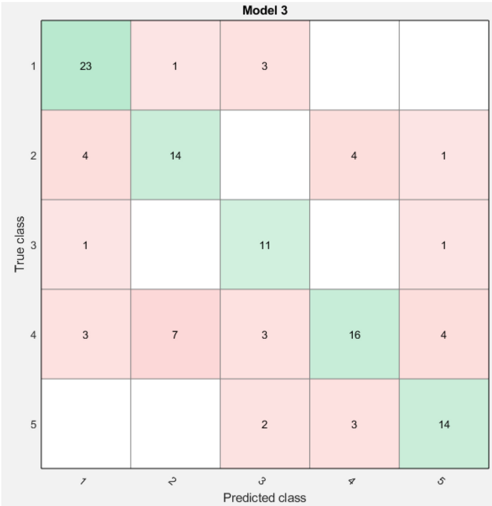


Fig. 7. Confusion Matrix given LBP with LDA for Lowest Recognition Accuracy for Desmids

5 Conclusion

In this paper, we studied the problem of automatic classification of desmids. To solve this problem, we have studies the behavior of three texture descriptors such as Histogram of Oriented Gradients, Local Binary Patterns Local Phase Quantization and with three classifiers namely Nearest Neighbor Classifier, Support Vector Machine and Linear Discrepant Analysis. During our experiments we have observed that Histogram of Oriented gradients and SVM is the best choice for classification of desmids. In future we will extended our work Deep Learning techniques.

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Authors' Contributions. Rajmohan Pardeshi carried out the experiment and wrote the draft manuscript. Rita Patil and Nirupama Anasingkar edited the draft and verified the results. Prapti Deshmukh Mam supervised the project. All authors discussed the results and contributed to the final manuscript.

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