Morphology-based identification and classification of Pediastrum through AlexNet Convolution Neural Network

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Abstract. In general solutions and outcomes to an issue in image processing, a ton of trail and examination with an enormous assortment of test photographs is incorporated. Pediastrum, which comprises of pigments like carotene, xanthophyll, chlorophylls, and other nourishing elements like complex sugars, major and minor minerals, and protein, enzymes, fiber, is a minute coccal shaped colony forming green algae. In this research, an attempt was made to solve the problem of identifying and classifying different species of Pediastrum with the aid of CNN based deep learning model. The informational collection comprising of 12,000 algal pictures was being utilized by, AlexNet CNN (Convolution Neural Network) model for the training and validating purposes. The features like the presence of sporopollenin in the cell wall, the structures and the functions of the cells, and the structural properties of coenobia make the basis for automated classification by AlexNet deep learning model. The efficacy of the proposed approach is demonstrated by an experimental outcome of 99.54 percent classification accuracy with precision and F1-score more than 0.98.

Keywords: Convolution Neural Network (CNN), AlexNet, Image processing, Coenobia, Pediastrum, Deep learning

1. Introduction

In a lentic aqua ecosystem with still waters such as the pond, basin marshes, ditches, reservoirs, seep, lakes, pools, puddles, lakes, etc. the presence of Pediastrum is often recorded, but mostly in the globe's tropical and equatorial regions with warm environment [1, 2]. Organisms in the genus Pediastrum are normally collected and formed star shaped colonies with flat appearance known as coenobium [3].Different species of Pediastrum has been classified on the basis of cells appearance and their arrangement which leads to the formation of different types of coenobia [4]. Pediastrum, a chlorophyll containing green algae with photosynthetic properties, transforms atmospheric CO2 into complex organic compounds such as polysaccharides, lipids, proteins and has unique properties of adaptation to different stressful environments [5]. Pediastrum has the potential to absorb inorganic wastewater nutrients (municipal sewage and industrial effluents) similar to cyanobacteria, making it a valuable and powerful contender for a pollution free sustainable ecosystem [6, 7]. While there is a lack of in-depth learning studies to recognise and classify Pediastrum species, however it is being used for some algae which belongs to different genus. Promdaen et al. [8] achieved 97.22 percent accuracy of classification with a group of 12 different microalgae commonly present in Thailand's water supplies.
through an automated recognition method based on the Sequential Minimal Optimization (SMO) technique's feature combination approach. Li et al. [9] applied the deep learning models on a data set contain 10,463 algal images and got a result with 97% classification accuracy by CNN based Mueller matrix imaging system. Deglint et al. [10] achieved 96% accuracy with six algal genera classification by applying a CNN based pre-trained deep learning model. While Park et al. [11] achieved a F1-score of 0.95 when applied the CNN based model for identification and classification of eight algal genera with watersheds as their habitat. In present scenario, a differential diatom separation method consisting of dataset as 126 images result in an estimated sensitivity of 95 percent, with 60% and 57% precision and accuracy respectively by Santaquiteria et al. [12]. To distinguish and classify the various species of Pediastrum on the morphological basis is still a cumbersome task. To target the above discussed challenges, this study target the four Pediastrum species, including Pediastrum duplex var. Gracillimum, Pediastrum simplex, Parapediastrum biradiatum, Pediastrum angulosum for classification and identification with the aid of CNN based AlexNet deep learning model. In comparison to the preeminent morphological feature selection-based classification of machine learning, deep CNN techniques pick features based on each layer's filter and kernel size, in addition to checking network over fitting [13]. In the future, such efficient facilities will leads to a new horizon for the improvement of an exceedingly efficient computer-based algal identification system.

2. Material and methods

2.1. Proposed method

With an achievable aim, this research is an effort to identify and classify the different Pediastrum species through a deep learning based automated image classifier. The modified AlexNet CNN model has been applied as a proposed deep learning model for this research. The components of the modified AlexNet are as follows.

**Input Layer:** There is always a layer in each deep learning model to receive the images and resize them for pulling out the important features to transfer them in other layers. It is always present as first layer and act as an input gateway.

**Convolution Layer:** After that, input layer data is being transferred to upcoming layers and they all are considered as convolution layers that serve as image filters, thus finding features from images and also being used during testing to measure the match feature points [20].

**Pooling Layer:** The sets of features extracted in the previous layers are now being transfer to the upcoming layers called as 'pooling layer.' The function of this layer is to extract and shrinks outsized images while retaining the most significant data in them. It also checks the model from picking up a maximum value and does not allow it to be set. The best fits for every function has been retained inside the each operating system which is generally a window.

**Rectified Linear Unit Layer:** The function of this unit is to alter or substitute the negative number if any of the pooling layer by 0. ReLU allow the model to keep on mathematically unswerving by being fixed to near 0 driving or up to a value of infinity.

**Fully Connected Layer:** At the final stage a group of fully connected layers is present and the function of this is to filter out the high-level images and modify them through labelling.
Fig1. AlexNet architecture for classification of bloom forming algae

The following steps are followed by proposed AlexNet model as:

1. Dataset preparation for Training and Validation: The images of finest categories were selected to use for training purpose and resize those into (224,244) pixels for AlexNet deep learning model and in later stage the dataset is being split into two assemblies, i.e. data sets for training and testing purpose.

2. Modifying the CNN network: Substitute the last three network layers by a group of completely connected layers, known as softmax layer. For the final classification completely linked output layer must be the equal in size as the number of groups in the data set applied during training period. The learning rate variables must be increased to train the network more quickly from the fully connected layer.

3. Network training: Set the training options as per the GPU requirement of the computer system, including rate of learning, sizes of the mini-batches, and testing details. Using the training data train the network.

4. Test the network accuracy: In this step an effort has been done to identify the testing images with the help of a fine tuned network and later the classification accuracy has been measured.

3. Results and discussion

3.1. Data set

The algal genera used in this study are having similar morphological characteristic. Due to this classification task is very difficult. Therefore, a suitable deep CNN model have been proposed for this study. The algal genera images were collected from different open source and past study. The original dataset contains 200 image of the Pediastrum. Since the size of the dataset is small, we have applied data augmentation technique to increase the size of the dataset.

3.2. Data augmentation

The data augmentation technique available in keras has been used to increase the number of samples in the dataset. The horizontal flip, vertical-flip, rotation (30°), zoom (30%) and shear (10%) is applied on each algal image [14,19]. After this the size of the augmented dataset is increased to 12000. In which each of the four class contains 3000 images. Finally, dataset was randomly split into 80% for the training and 20% for the testing.

3.3. The Training and Testing Evaluation
The proposed model is trained with input image of 224x224 with a batch size of 32 and an initial learning rate of 1e⁻³. The loss of the model is calculated using categorical catastrophe and compilation is performed using Adam optimizer. Finally, the model is trained for 100 epochs. After completion of training, performance of the model is evaluated using losses and accuracy losses. The training and testing accuracy as well as loss are shown in the figure 2.

![Graphical representation of accuracy and loss on augmented dataset by the proposed model.](image)

3.4. The error matrix

A confusion/error matrix was plotted to measure the output of the proposed method. The instances in a predicted class are expressed in each matrix row, while each column represents the actual instance of the class [15,18]. It can be noticed in the confusion matrix that the eleven images have shown their affinity with both Lacunastrum gracillimum and Monactinus simplex. It may be because of the similarities in oval or cylindrical shape and similar number of 8 to 16 cell in coenobia. The detailed error matrix is shown in the figure 3.

![Confusion Matrix](image)

**Fig3.** The error matrix for the applied model.
3.5. F1-score

The harmonic mean of accuracy and recall was also determined in addition to the error matrix for the accuracy demonstration. The model's success was assessed by accuracy, recall, and F1-score. Due to a high level of morphological similarities in between Monactinus, Lacunastrum gracillimum simplex, the value of F1 score are 1.0, 0.99 and 0.99 respectively. The resulted outcomes of the proposed model are shown in the Table 1.

Table 1. Resulted outcomes of the proposed model.

| Algal Species   | precision | recall | f1-score |
|-----------------|-----------|--------|----------|
| gracilimum      | 0.98      | 1.00   | 0.99     |
| simplex         | 1.00      | 0.98   | 0.99     |
| biradiatum      | 1.00      | 1.00   | 1.00     |
| angulosum       | 1.00      | 1.00   | 1.00     |

4. Conclusion

A deep learning-based algorithm was used in the present research to design a CNN based auto classifier for the Pediastrum identification and classification to decrease time and reliance on an algal specialist by modifying topology of AlexNet CNN. The results of the proposed model is significantly high on the augmented dataset. The efficacy of the proposed model is determined by a high training accuracy, validation accuracy and F1-score 100%, 99.54% and 99.99%, respectively. This efficiency is even higher than the up-to-the-minute approaches. There is a motivation for us to add more algae groups for the identification and categorization in a future report. The suggested models also need to be checked on the other dataset in order to further assess the system's performance.

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