EasyChair Preprint

№ 7234

Multiclass-Classification of Algae Using Dc-GAN and Transfer Learning

Ziaullah Khan, Abdullah, Wajid Mumtaz, Hee-Cheol Kim and Abdul Samad Mumtaz

December 17, 2021

Multiclass-classification of Algae using Dc-GAN and transfer learning

Ziaullh Khan
National University of Science and Technology Islamabad, Pakistan
zkhan.msee19seecs@seecs.edu.pk

Mr. Abdullah
Institute of Digital Anti-Aging Healthcare, Inje University, Gimhae 50834, Korea
Abdullahbaltistani@gmail.com

Wajid Mumtaz
School of Electrical and Computer Engineering, National University of Science and Technology Islamabad, Pakistan.
Wajid.mumtaz@seecs.edu.pk

Hee-Cheol Kim
Institute of Digital Anti-Aging Healthcare Inje University, Gimhae 50834, Korea.
heeki@inje.live.ac.kr

Abdul Samad Mumtaz
Department of Plant Science, Quaid-i-Azam UniversityIslamabad , Pakistan
asmumtaz@qau.edu.pk

Abstract*:** ***The growth of algae is a natural process and highly increase in concentration having a bad impact on water bodies as well as other creatures. The monitoring and classification of algae by using the traditional method is a tedious and time-consuming task. The reliable and robust development of the alternative method is crucial to do these tasks, however, advanced machine learning and deep learning are excessively used to address this problem. In recent years the transfer learning method is getting more attention and extensively used by people for features extraction and classification purposes but due to high variation of environment, low-quality input images and different varieties of algae plants still create gaps for the researcher. To build a robust and reliable system all these factors should need to be considered. In this paper, we have used the transfer learning technique, in which various pre-train models are used to train on our custom dataset. We experiment to classify four genera of harmful algae bloom (HAB), furthermore, we compare each pre-train architecture performance on our unique dataset. The proposed model effectively classifies, and overall accuracy is 98.07 %. The transfer learning model approach would be an effective tool for rapid operational response to algae bloom events. The experimental results show that the proposed method is more effective and reliable to detect and classify the algae.

Keywords: ***transfer learning, pre-train model, HAB, classification***

1. Introduction:

Algae is a plant-like organism, which is normally occurred inside the pond, lakes, and rivers. The HAB is a natural phenomenon and increased in its concentration forms colonies and cover a wide range of area, which is very dangerous for water bodies as well as other creatures. It generates a variety of bioactive compounds and toxins, which is very harmful to a living organism. It is very important to identify by monitoring its growth and concentration to take safety action against it. The overgrowth of algae is called algae blooms, it is a constant global problem that affects the water management in freshwater bodies for many decades. It influences by many physical factors like temperature, nutrients, sunlight, and climate change [1-2]. The intensity and high concentration of HAB cause diseases in marine as well as human life because algae bacteria produce toxins and harmful compounds like neurotoxic, amnesic, and paralytic in water bodies, in addition, shellfish poisoning is caused by azaprocin toxin, it is also dangerous for aquatic creatures [3]. Hence, it is important to take a step to save aquatic life and maintain the quality of freshwater for other water-dependent bodies, so it is necessary to monitor and identify the production of HAB in lakes, rivers, and pound to take prompt action. Currently, the conventional method for this job needs manpower, which is a tedious and highly expensive task while on the other hand AI-based model help to do this task in a more efficient way. The study conducted by Culverhouse et al [4] that the recognition of human taxonomists accuracy is nearly between 67% and 83%, it also depends on taxonomists.

The convolutional neural network (CNN) based model and multilayer perception (MLP) is used to detect and analyze the presence of algae inside the water pipeline [5], In addition, MLP and CNN models are compared to study different perspectives by using video data. Transfer learning is the most popular and new paradigm in the domain of machine learning and deep learning that help to solve various problems. In addition, this model is purely based on the CNN model, which is already trained on the various domain of the labeled dataset and can be used to extract features from new different datasets. This model helps to detect generic features from the lower layer of the model network; however, the higher model network layer is used to extract a particular network. This idea behind the pre-trained model enables to recognized and classify new objects from any image dataset [6].

In this study, we have used transfer learning pre-trained models to identify and classify the four types of green algae namely Closterium, Cosmarium, Scenedesmus, and Spirogyra. We have used multiple pre-train models to analyze the performance of each model against each class and compare our proposed model with the current existing model. As transfer learning is a powerful and advanced technique in the field of AI, furthermore this method saves memory and time consumption to fully train it. In this paper our main contribution is the collection of raw images data, pre-processing of input images, and train the model by freezing the top few layers to get better accuracy and make it applicable for future application. This work is organized as follows: Section 2 illustrates the overview of related work, section 3 demonstrates the methodology, which includes, explanation about the dataset, pre-processing method, and architecture we used, section 4 present the result and discussion of the proposed model, the conclusion and future work will explain in section 5 and section 6 respectively.

2. Related work

Algae blooms occur in the freshwater reservoir, lack, pound, and coastal waters, the increase in its growth absorbed oxygen and stop the sunlight to reach the underwater plant. It also produces undesired able toxins and compounds which are harmful to human health. Cyanobacteria expansion and persistence are caused by global warming, change in climate, and high temperature. HAB is very dangerous from the perspective of surroundings, water bodies, and human health. In the last decade, multiple research conducted to identify and classify to mitigate the excessive growth of algae plants. Zamyadi et al. [7] study to control and reduce the effects of algae bloom on freshwater ecosystems are essential for ensuring the safety of drinking water supplies monitoring the frequency and the

physiological state of the bloom is vital to develop efficient for managing water resource. In a wide region, the detection of algae blooms can be possible through monitoring by aerial aircraft using hyper-spectral or multi-spectral images taken from drones, aircraft or satellites has been proven to be a successful method [8-10]. Whereas constant and direct monitoring is necessary for quick and efficient operational responses within water management districts and services for processing drinking water to prevent unintentional algae bloom. This study also focuses on the visual inspection with a microscope is among the more common and widely used methods of the identification of algae species, however, it is long-lasting and requires a lot of workers. In addition, the result could be subjective and can be affected due to the experimenter's fault. So, the creation of a new method is essential for efficient and accurate identification of the unintentional algae bloom.

In the past decade, a lot of studies conducted to address the HAB, that it blooms due to various factors like climate change, an increase of temperature, changes in pH values, and salinity [11]. Furthermore, the large number of algae species are not directly harmful in low concentration, while when its concentration is increased then it became dangerous for both aquatic and human life. The continuous realizing of toxin by algae for a long period cover the surface of the water, which reduces sunlight infiltration and badly affect the processes of photosynthesis and destroy the aquatic environment, furthermore, it also consumes enough quantity of oxygen, which cause the death of water bodies [12]. When algae blooms growing goes out of control, some algae produce harmful toxins, which destroy the life of water bodies, birds, and in extreme cases occur human death, while other algae did not produce toxin, but they consume all oxygen. This is a common national issue because it affects the marine ecosystem as well as human health. Cyanobacteria HAB generates highly toxic compounds, the increasing quantity of cyanotoxins in freshwater is cyclic heptapeptides of microcystins [13]. It controls the cell cycle, proteins synthesis, and neurotransmission in living things. The HAB toxin contains a microcystin congener with various amino acids. The study conducted by Gobler [14] on HAB and Cyano-HAB spread drastically due to climate change, eutrophication, drainage, and dams. All these blooms produce harmful toxins and destroy the ecosystem, water bodies, and other creatures.

In all these previous studies, no one used a transfer learning-based model to address this classification problem. Nowadays transfer learning-based model is the most powerful and popular tool to address various kinds of problems. Especially in image analysis problems, it is extensively used by the researcher. The direct generative adversarial network Dc-GAN [15] is also one of the famous and advanced techniques to handle a smaller number of images. In our study we have used GAN and transfer learning method, in which the pre-train model is already trained on ImageNet dataset, we have used that architecture as backbone model in our experiment to classify algae species belonging to different four classes and try to compare various pre-train architecture on our custom dataset

3. Research Material and Methodology

This section describes the method and experiment in detail of this research work.

3.1 Collection of dataset and Preprocessing

The original dataset consists of 400 microscopic images belonging to 4 classes namely Closterium, Cosmarium, Scenedesmus, and spirogyra. These algae are cultivated in the main laboratory of Quaid-Azam international University Islamabad, the water sample are taken from the laboratory and collected microscopic images with the help few university students. To train a deep learning model the number of images is too low, So in this case it is very difficult to apply a transfer learning pre-train model on such a small dataset.

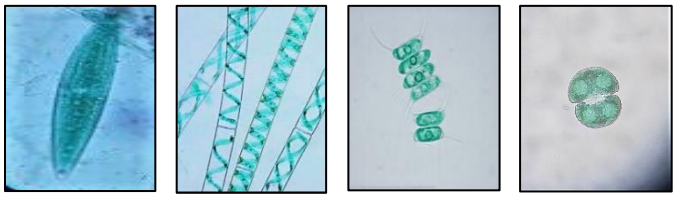


Figure 1. Microscopic image of Algae

Figure 1. Shows the algae microscopic original images and each image belong to different classes. To overcome the deficiency of the dataset, we adopt the data preprocessing technique in which, we used traditional and advanced data augmentation methods. In the advanced data augmentation method, we have used a popular deep learning-based framework GAN, which is trained on our original images and generates new data with a similar statistic as our training set. The GAN framework getting more and more attention, due to its robustness and high output quality. As we apply data augmentation and Dc-GAN, we get 800 images in each class. This huge data enable us to well train our model more accurately.

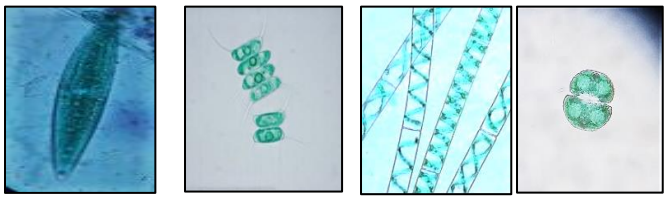


Figure 2. Dc-GAN Generated Algae Images

DC-GAN is an advanced form of GAN, which is getting more and more attention in image processing and computer vision domain. In this work, we used DC-GAN to generate more images similar to original data as shown in figure 2. It is very clearly seen that there is not too much difference between original data and generated data. The DC-GAN used a convolutional layer instead of the max-pooling layer, similarly in discriminator part used the global average pooling layer in place of the fully connected layer. The batch normalization process is used on both sides of the discriminator and generator, furthermore, in the discriminator part, a leaky Relu activation function is used. The generator and discriminator network are similar to a mirror. So, in this way, we can generate a lot of similar images to solve any problem

3.2 CNN Based Framework

Transfer learning-based method is the concept of CNN-based pre-train models, which is already trained on a large number of the dataset, and it learned features from that dataset, furthermore, we used this model to solve our problem. In transfer learning, the parameter of the model is transferred which speeds up the speed of convergence and increases the robustness of the model. All models are the combination of three main layers, convolution layer, pooling layer, and fully connected layer. In the architecture, the kernel and stride size are the most important parameters because it performs convolution to obtain valuable features. In the pooling layer, it minimizes the complexity by reducing the number of parameters, similarly, the fully connected layer connects all the previous layers' output simply. The main idea behind

these pre-train models is based on two types of features which are general features and specific features. All these models are well trained on millions of images with high accuracy, so we can use these architectures on our custom dataset to get more accurate results. We freeze a few top layers of this model and add new layers according to our requirement to train on our dataset, which gives more specific features and the rest of this framework produces general features. Both features are combined to help to produce more good results.

The pre-train model VGG16, restnet18, Google net, and Inception are CNN-based model, which is extensively used for image classification and analysis of images. We have used these four deep learning-based architectures to analyze our custom algae microscopic image dataset. In this regard, we have frozen the last top few layers and used the rest of the framework as it is to train the model. We adjust hyperparameter values of all models according to our needs. We used Relu as an activation function, stochastic gradient descent (SGD used as an optimizer, the learning rate is 0.001, the batch size is 12 and epoch is 10. We choose these parameters based on output performance.

To train these model the microscopic original image data is used as input to train Dc-GAN, which generate almost 3200 combinedly real and fake images. Furthermore, these images are pre-processed by removing noise and resizing the images according to each architecture requirement. The VGG16, Google net, and RestNet18 model required input image size is 224 X 224, similarly, the Inception v3 model required 299 X 299 image size. Furthermore, we have normalized the image data and split the normalized dataset into training and testing set with 80:20 ratio. Then we have trained the model to classify as shown

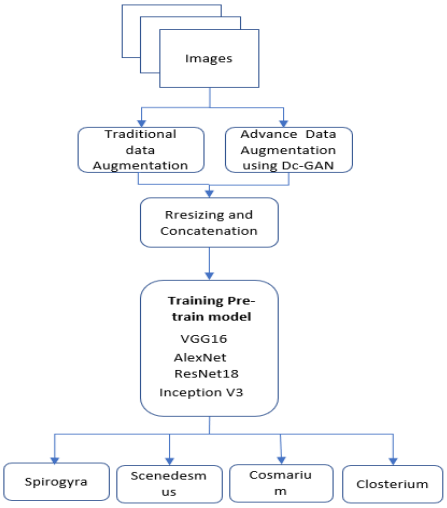


Figure 3. Block Diagram of workflow

The concept of transfer learning technique is more fruitful in many ways. It help to get a more accurate result and required minimum time to fully train the model as compared to training from scratch. We just train a few top layers and get the effect of the whole architecture in the output results, that is the beauty of these architectures.

4. Experimental Result and Discussion

This section illustrates the finding and results of this experiment. We have represented all the experimental results in the form of a confusion matrix, training-testing accuracy and loss curves, and the overall accuracy of each pre-train model.

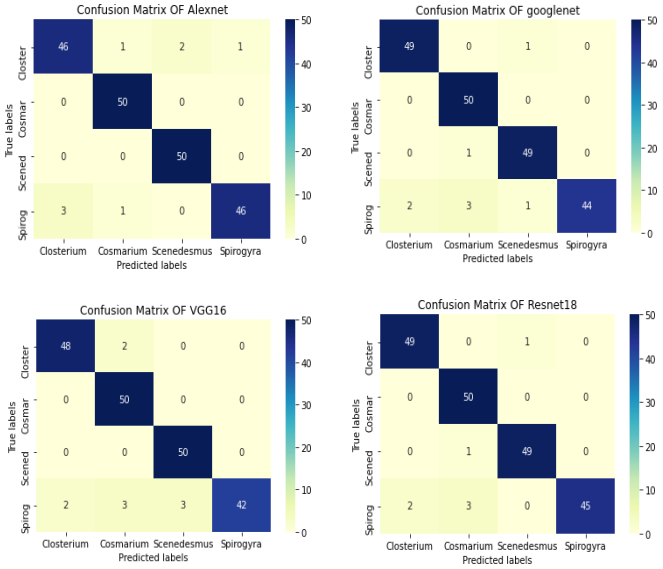
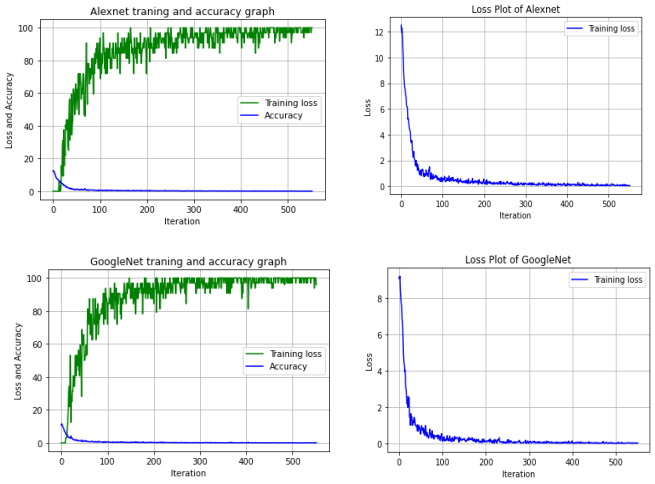


Figure 4. confusion matrix of different frameworks

Figure 4. Illustrate the confusion matrix of Alexnet, google net, VGG16, and Restnet18 respectively. The confusion matrix is the tabular representation and summary of each model. It shows the true and false values predicted by the classifiers. It gives better intuition regarding the performance of the models. The confusion matrix is a two-dimensional matrix, one dimension shows the actual classes, and the other dimension shows predicted classes. As shown in figure. 4 on the y-axis, it represents the actual classes and similarly, on the x-axis, it represents predicted classes of each model. The diagonal value is our more concerned value, which represents the algae classification rate of each class. In the given figure. 4, we can see all the four models diagonal values are more prominent

Table 1. Comparison of models and accuracy

Models	Accuracy %
Inception V3	96.16
Google net	96.35
Rest Net 18	97.10
VGG16	98.07



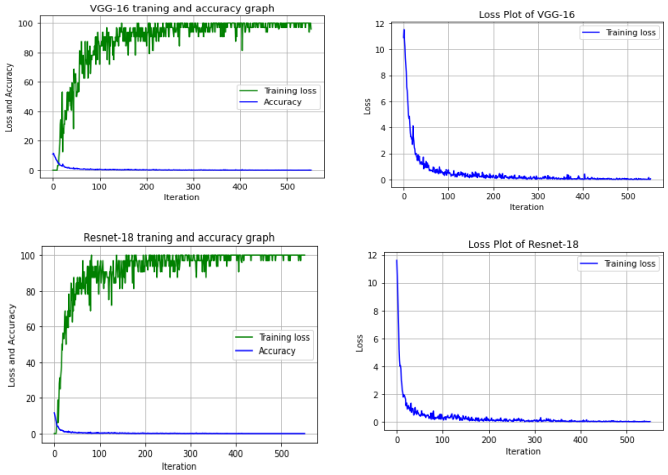


Figure 5. Graphical representation of training and accuracy of various model

The table.1 show the comparison and accuracy of each model . The inceptionV3 model with 96.16% accuracy, similarly, Googlenet on the same images is 96.35% accuracy, furthermore, Restnet18 and VGG16 model performance is more acceptable and can be able to use in real applications with an accuracy of 97.10% and 98.07% respectively. The graphical representation of training accuracy and loss of various four models is nearly similar to each other, which is shown in fig 5 ; In addition, the loss is very near to zero. In the previous study, no one used transfer learning to classify the algae microscopic images, whereas they used various techniques to do the same job but still the most of the model performance is not too good as compare to our suggested model. So, in this consequence, our proposed model is robust and helpful for the world community in the field of research .

5. Conclusion

The algae bloom is an alarming situation for aquatic life and water-dependent creatures. It is necessary to take proper steps against its growth. It destroys the ecosystem of water bodies. In this consequence, we have to build a continuous monitoring system for algae bloom in the pond, river, lake, and other water reservoirs. As it is tedious and high expenses to do it by manpower, but advanced machine learning and deep learning play a vital role to address this problem simply and easily. In this regard, we have performed some experiments to classify the algae microscopic image to differentiate according to their respective classes. we used the transfer learning method, in which pre-train models are trained on a custom dataset to predict it accurately. The performance of all models we have used on the same custom dataset is outstanding. Furthermore, we have proposed transfer learning-based VGG16 model performance is 98.08% accuracy, which is more suited to perform classification as compared to the other three. Transfer learning techniques reduce our training time as well as our processing power consumption, so this is quite good for further experiments.

6. Future work

In the future, we can extend this work by employing Yolo4 and Yolo5 to detect algae from microscopic images, similarly, we can do the same work for video or real-time streaming video. We can explore the various architecture of the deep neural network. This involved analyzing the different advanced networks which can automatically identify and classify a large number of algae in freshwater. In future work, we can include more specifications like developing a real-time system that can identify the algae bloom and present the concentration of that particular algae species.

References

[1] Dauta, A., Devaux, J., Piquemal, F. and Boumnich, L., 1990. The growth rate of four freshwater algae concerning light and temperature. *Hydrobiologia*, *207*(1), pp.221-226.

[2] Paerl, H.W. and Otten, T.G., 2013. Harmful cyanobacterial blooms: causes, consequences, and controls. *Microbial ecology*, *65*(4), pp.995-1010.

[3] Anderson, D.M., 2009. Approaches to monitoring, control, and management of harmful algal blooms (HABs). *Ocean & coastal management*, *52*(7), pp.342-347.

[4] Culverhouse, P.F., Williams, R., Reguera, B., Herry, V. and González-Gil, S., 2003. Do experts make mistakes? A comparison of human and machine identification of dinoflagellates. *Marine ecology progress series*, *247*, pp.17-25.

[5] Medina, E., Petraglia, M.R., Gomes, J.G.R. and Petraglia, A., 2017, November. Comparison of CNN and MLP classifiers for algae detection in underwater pipelines. In *2017 Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA)* (pp. 1-6). IEEE

[6] Shin, H.C., Roth, H.R., Gao, M., Lu, L., Xu, Z., Nogues, I., Yao, J., Mollura, D. and Summers, R.M., 2016. Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics, and transfer learning. *IEEE transactions on medical imaging*, *35*(5), pp.1285-1298.

[7] Zamyadi, A., Choo, F., Newcombe, G., Stuetz, R. and Henderson, R.K., 2016. A review of monitoring technologies for real-time management of cyanobacteria: Recent advances and future direction. *TrAC Trends in Analytical Chemistry*, *85*, pp.83-96.

[8] Goldberg, S.J., Kirby, J.T. and Licht, S.C., 2016. Applications of aerial multispectral imagery for algal bloom monitoring in rhode Island. *SURFO Technical Report No. 16-01*, p.28.

[9] Kudela, R.M., Palacios, S.L., Austerberry, D.C., Accorsi, E.K., Guild, L.S. and Torres-Perez, J., 2015. Application of hyperspectral remote sensing to cyanobacterial blooms in inland waters. *Remote Sensing of Environment*, *167*, pp.196-205.

[10] Lekki, J., Anderson, R., Avouris, D., Becker, R., Churnside, J., Cline, M., Demers, J., Leshkevich, G., Liou, L., Luvall, J. and Ortiz, J., 2017. Airborne hyperspectral sensing of monitoring harmful algal blooms in the Great Lakes region: system calibration and validation.

[11] O'neil, J.M., Davis, T.W., Burford, M.A. and Gobler, C.J., 2012. The rise of harmful cyanobacteria blooms: the potential roles of eutrophication and climate change. *Harmful algae*, *14*, pp.313-334.

[12] Anderson, D.M., 2009. Approaches to monitoring, control and management of harmful algal blooms (HABs). *Ocean & coastal management*, *52*(7), pp.342-347.

[13] Vogiazi, V., de la Cruz, A., Mishra, S., Shanov, V., Heineman, W.R. and Dionysiou, D.D., 2019. A comprehensive review: Development of electrochemical biosensors for detection of cyanotoxins in freshwater. *ACS sensors*, *4*(5), pp.1151-1173.

[14] Gobler, C.J., 2020. Climate change and harmful algal blooms: insights and perspective. *Harmful algae*, *91*, p.101731.

[15] https://pytorch.org/tutorials/beginner/dcgan_faces_tutorial.html