Automated Classification of Harmful Phytoplankton Using CNNs and Transfer Learning Approaches

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I Introduction:

Phytoplankton forms the foundation of aquatic ecosystems, playing a crucial role in energy transfer and producing around 90% of Earth's oxygen. Low plankton levels pose a threat to ocean ecosystems, while excessive growth can lead to harmful algal blooms (HABs) that release toxins, affecting both the environment and public health. Species such as Aphanizomenon, Microcystis, Anabaena, and Oscillatoria produce toxins that can contaminate water supplies and harm animals and humans.

Phytoplankton is also sensitive to environmental changes and serves as an indicator of global warming and water anomalies like eutrophication. Monitoring phytoplankton is essential for maintaining aquatic ecosystems and regulating climate. However, traditional monitoring methods are time-consuming, costly, and require skilled professionals, making them impractical for large-scale use.

To address these challenges, researchers are turning to automated plankton classification using deep learning, particularly Convolutional Neural Networks (CNNs). Studies have successfully applied models like AlexNet, VGG16, ResNet50, and MobileNetV2 for identifying harmful phytoplankton, while others used Faster R-CNN and ensemble learning to recognize various plankton species.

The objective of this study is to develop an automated system for toxic phytoplankton recognition using CNN models such as ResNet, ResNeXt, DenseNet, and EfficientNet. The study explores three transfer learning strategies: linear probing, fine-tuning, and a combined approach, aiming to improve the accuracy and efficiency of plankton monitoring.

II Short Summary:

For this study, we used a publicly available phytoplankton dataset (Yang et al. 2023), which includes images of eleven harmful phytoplankton genera. The dataset contains a total of 1650 images, both original and augmented, with each class represented by 150 RGB images resized to 224x224 pixels. The images were sourced from "the-algae-cell-images" webpage. We divided the dataset into three subsets: training data for optimizing model parameters, validation data to select the best model and prevent overfitting, and test data to evaluate the model's ability to generalize.

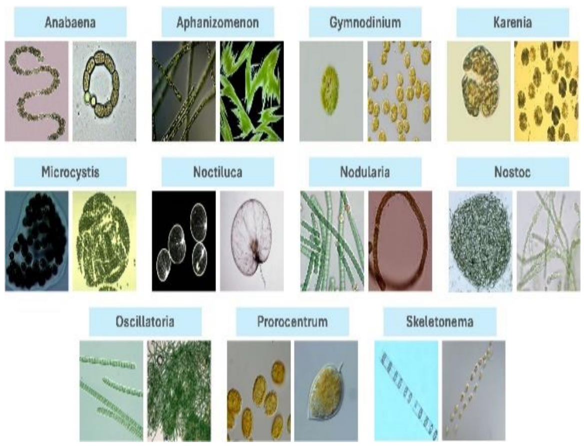

Figure 1: Visualization of two samples per class from the toxic phytoplankton dataset.

We employed transfer learning to build an automatic phytoplankton recognition system, exploring three different approaches. First, we applied Linear Probing, where the model's backbone was frozen, and only the classifier head was trained for 100 epochs.

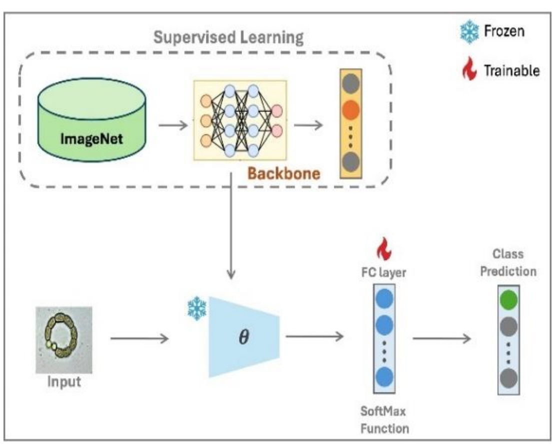

Fig. Learning approach using linear probing

Second, we used Fine-Tuning, training both the backbone and classifier head for 100 epochs.

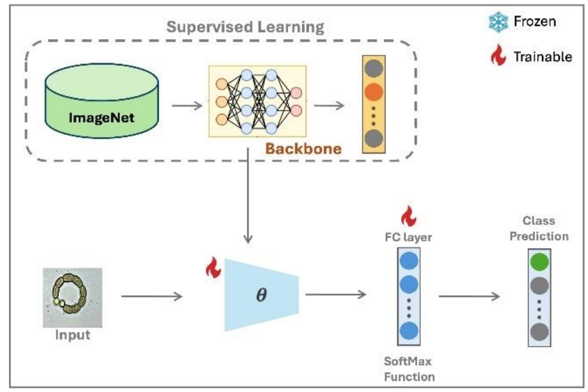

Fig. Learning approach utilizing fine-tuning

Lastly, we implemented a Combined Approach, training the model with linear probing for 50 epochs at an initial learning rate of 0.001, followed by fine-tuning for another 50 epochs at a lower learning rate of 0.0001.

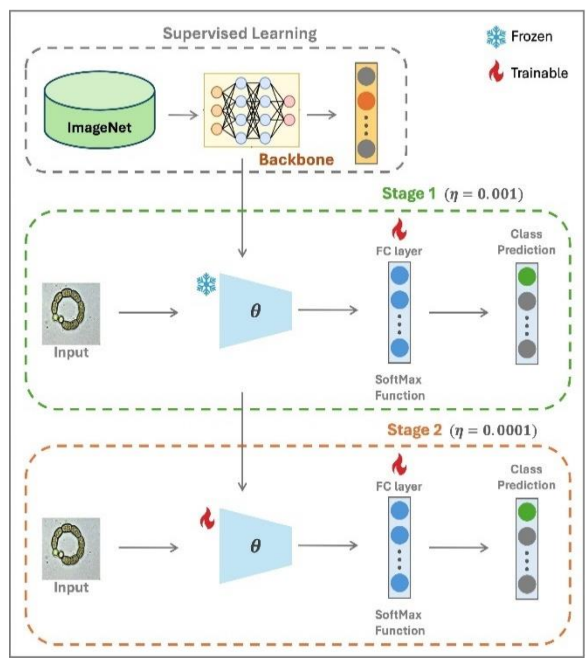

Fig. Learning approach that integrates both linear probing and fine-tuning.

We tested several CNN backbones with varying batch sizes and learning rates. All models were pretrained on ImageNet, and we used the Adam optimizer for the classification task, adapting the classifier heads to handle the eleven phytoplankton classes. To assess the model's performance, we used three metrics. Precision was used to measure the accuracy in identifying phytoplankton genera, recall evaluated the model's ability to retrieve instances of each genus, and accuracy was used to determine the proportion of correctly classified images across the dataset.

III Results and Critical Analysis:

The below figure illustrates the validation results of training the ResNet-50 model using a combined transfer learning strategy across different batch sizes (4, 8, 16, 32, and 64). The best performance, with an accuracy of 95.3%, was achieved using a batch size of 8.

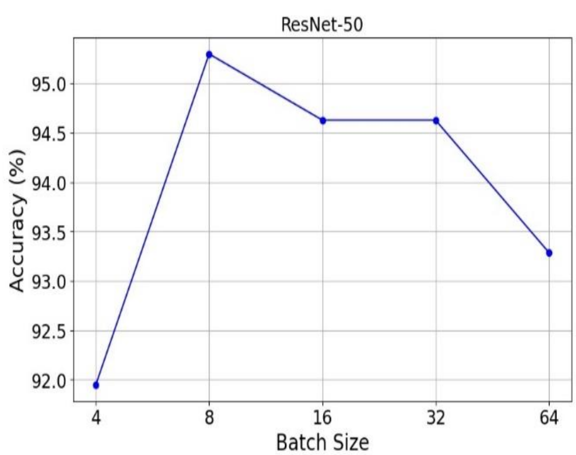

Fig. ResNet-50 accuracy on validation set across various batch sizes using a learning strategy that combines linear probing and fine-tuning.

Table 1 summarizes the validation results of training the ResNet-50 model with a batch size of 8 images using three learning approaches, with the fine-tuning approach and an initial learning rate of 0.0001 achieving the highest accuracy of 95.97%.

Transfer learning approach	Learning rate	Accuracy (%)
Linear probing then fine-tuning	0.001 - 0.0001	95.3
Linear probing	0.001	93.29
Linear probing	0.0001	92.62
Fine-tuning	0.001	89.26
Fine-tuning	**0.0001**	**95.97**

Table1: Evaluation of ResNet-50 on validation set across different learning designs trained with a batch size of 8 images.

Table 2 shows the test results for various CNN backbones trained with the fine-tuning approach, batch size of 8, and initial learning rate of 0.0001. ResNet-50 performed the best, reaching 96.97% accuracy, 96.99% precision, 96.97% recall, and completing training in 18.51 minutes.

Backbone	Accuracy (%)	Precision (%)	Recall (%)	Training time (min)
ResNet-18	93.33	93.56	93.33	12.75
ResNet-50	**96.97**	**96.99**	**96.97**	**18.51**
ResNet-152	95.15	95.58	95.15	35.5
ResNeXt-50	95.76	95.82	95.76	21.97
DenseNet-121	91.52	92.04	91.52	27.47
EfficientNet-B0	96.36	96.47	96.36	20.87

Table2: Evaluation of various CNN backbones on test data for phytoplankton recognition, trained with fine-tuning and a batch size of 8 images.

The model achieved 100% accuracy for most phytoplankton genera, except for four: Oscillatoria (85.71%), Aphanizomenon (90.32%), Nodularia (93.33%), and Anabaena (96.77%). The below shown confusion matrix for the test data, reveals key areas where the model struggled. Aphanizomenon was frequently misclassified as Nodularia, while Nodularia was often mistaken for Oscillatoria. Additionally, Oscillatoria was commonly confused with both Aphanizomenon and Anabaena. These misclassifications are largely due to the similar morphological characteristics shared by these four genera, making it difficult for the model to distinguish between them. Despite these challenges, the model performed well overall, with these genera representing the main sources of classification errors.

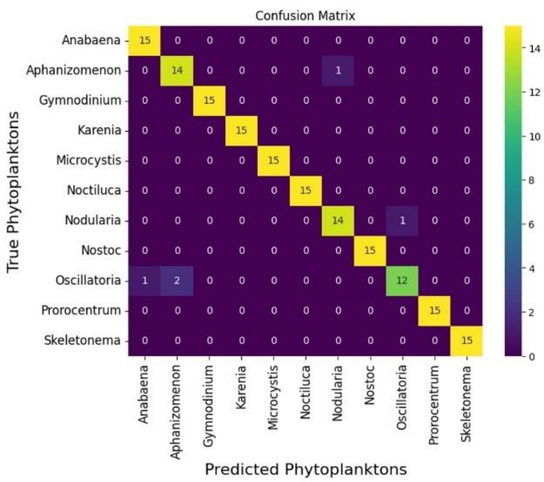

Fig. Confusion matrix displaying true and predicted phytoplankton class distributions on test data, generated by ResNet-50 trained with fine-tuning

IV Conclusion:

In this study, we assessed six CNN architectures—ResNet-18, ResNet-50, ResNet-152, ResNeXt-50, DenseNet-121, and EfficientNet-B0—using three transfer learning strategies: linear probing, fine-tuning, and a combined approach, to classify eleven harmful phytoplankton genera from a publicly available microscopic image dataset. The highest accuracy of 96.97% was achieved by ResNet-50 with the fine-tuning approach. However, the models faced challenges in distinguishing between four phytoplankton types with similar morphological features. The proposed system provides a useful tool for experts by automating species identification and minimizing manual effort. Still, the development of a more diverse dataset, covering a broader range of harmful phytoplankton species, is recommended to enhance model generalization for water quality monitoring.

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