

# CS583A: Course Project

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## 1 Summary

Problem descriptions: I participate in an inactive with late submission competition of classifying ocean species based on photos. Methodology: I try many architectures. The final model I choose is ResNet50, a deep convolutional neural network architecture, which takes  $64 \times 64$  grey images as input and outputs the class labels. Implementation: I implement the convolutional neural network using Keras and run the code on Colab with Google Compute Engine Backend (GPU). Evaluation metric: Performance is evaluated on the multi-class logarithmic loss. Score and ranking: In the public leaderboard, our score is 4.41216; we rank 746 among the 1049 teams. In the private leaderboard, our score is 4.41558; I rank 778 among the 1049 teams.

## 2 Problem Description

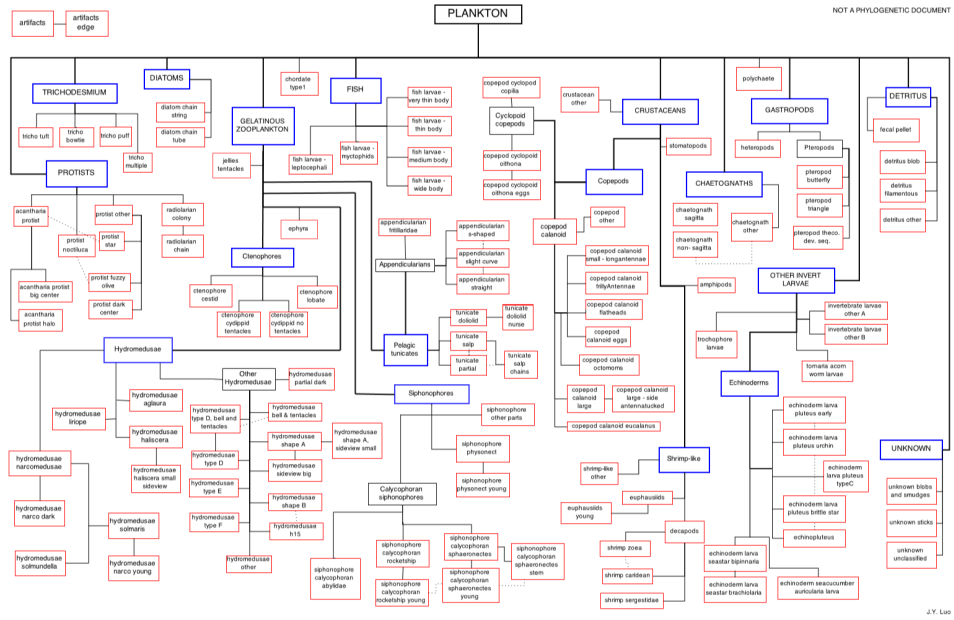
**Problem.** The problem is to classify species in ocean based on photos. This is a multi classification and image recognition problem. The competition is at <https://www.kaggle.com/c/datasciencebowl/>.

**Data.** The data are JPG gray-scale images in different size based on different species. The number of training samples is  $n = 30336$ . The number of testing samples is  $n = 130400$ . The number of classes is 121. One of the classification is 'Unknown' class. The training set is not balanced.

**Challenges.** There are many different species, from large fish to small plankton. Some of species are similar, some of species are still unknown. Image cannot represent 3 dimension structure of objects. The same species looks unlike in different direction. The training set is small. The number of common species are larger than rare ones.

## 3 Solution

**Model.** I use and implement 5-layer CNN, ResNet18, ResNet50. The model I finally choose is the ResNet50 [1], a standard deep convolutional neural network. A description of ResNet is online: [https://en.wikipedia.org/wiki/Residential\\_network](https://en.wikipedia.org/wiki/Residential_network). The input of standard ResNet50 is 3 channels images. I changed it to 1 channel to match the input of my grayscale image data. In the model output, I changed the number of hidden points in the fully connected layer to 121.



(a) The classification of dataset.

Figure 1: The classifications.

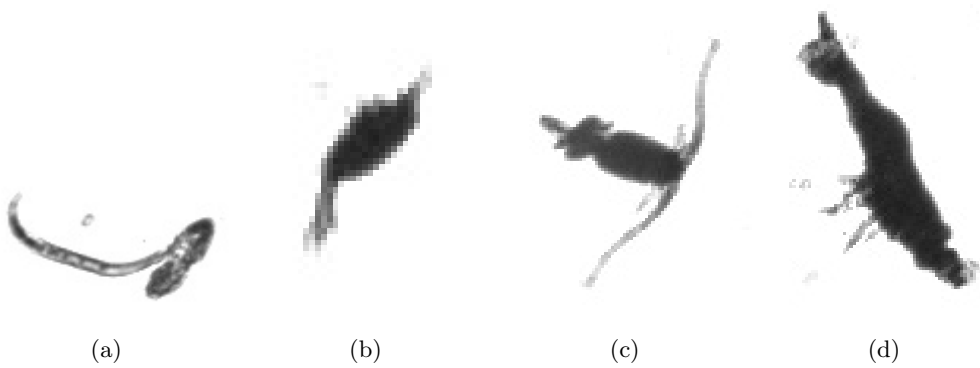
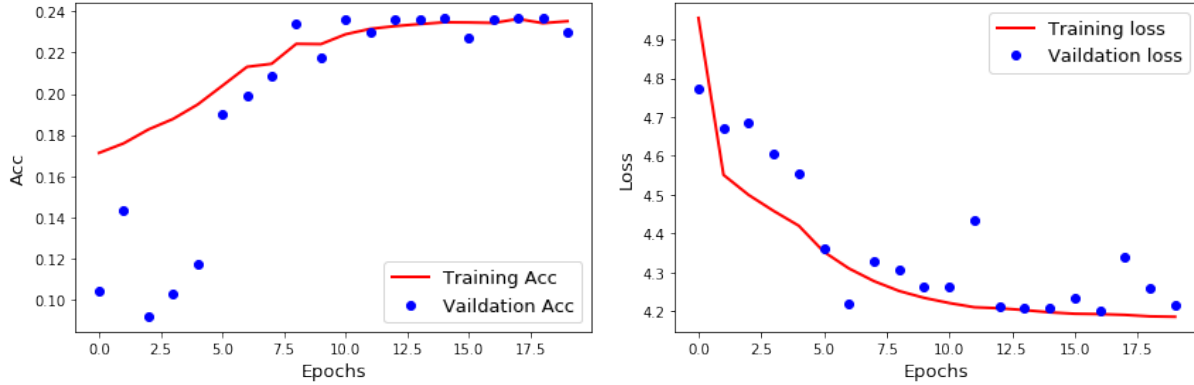


Figure 2: Some examples



(a) The classification accuracy on the training set and validation set. (b) The loss on the training set and validation set.

Figure 3: The convergence curves.

**Implementation.** I implement the 5-layer CNN, ResNet18, ResNet50 model using Keras with TensorFlow as the backend. My code is available at [https://github.com/Linzp721/CS583/blob/master/Project/CS583\\_CourseProject.ipynb](https://github.com/Linzp721/CS583/blob/master/Project/CS583_CourseProject.ipynb). I run the code on Colab with Google Compute Engine Backend (GPU).

**Settings.** The loss function is categorical cross-entropy. The optimizer is RMSprop. The learning rate is  $1E-3$ . The regularization is L2-regularization, rate is  $1E-4$ . The epochs is 20. The batchsize is 128.

#### Advanced tricks.

- Data augmentation. Feature and line in images are thin and light. First, I threshold the image on its mean value. Then, I dilate the image. Operation effect is shown in the figures.
- Over-sampling and Under-sampling. Because the data is imbalanced (The number of samples in different categories varies widely. Some categories examples less than 100, others more than thousands), I tried over-sampling and under-sampling so that the number of samples in each category is about 300.

**Validation.** I partition the training data to 80%-20% for hyperparameter tuning. Figure 3 plots the convergence curves on 80% training data and 20% validation data. Due to too many classifications, the accuracy becomes very low. So I used top-5 accuracy. From the convergence curves, accuracy increases and loss decreases with epochs. After 10 epochs, the curve gradient starts to decrease.

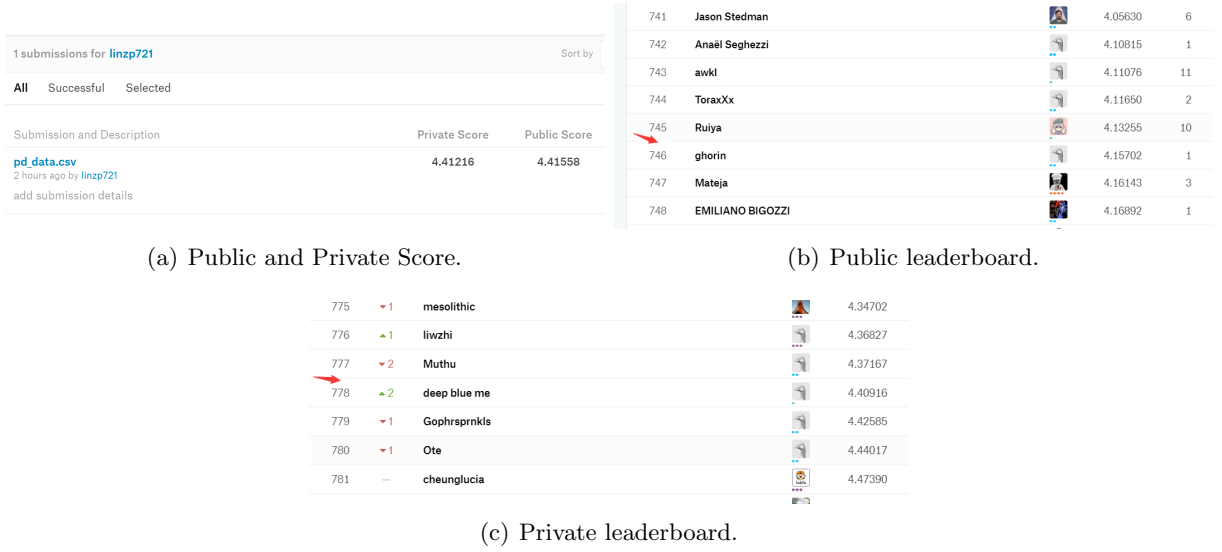


Figure 4: Public and Private Score, Leaderboard

## 4 Compared Methods

**ResNet50.** I use the ResNet50 model using Keras with TensorFlow as the backend. Its parameters are pretrained on the ImageNet dataset. The training and validation accuracies are respective 23.52% and 22.97%. The multi-class logarithmic loss value is 4.2044.

**ResNet18.** I implemented Resnet18 before implementing Resnet50. The residual block uses the Building block structure, while 50 uses the Bottleneck structure. The training and validation accuracies are respective 23.48% and 22.04%. The multi-class logarithmic loss value is 4.3041.

**5-layer CNN.** I implemented a 5-layer convolutional neural network with 2 Dense layers. I apply maxpooling and dropout in this model. The training and validation accuracies are respective 5.16% and 4.39%. The multi-class logarithmic loss value is 4.7826.

**Random guess.** I use random guess strategy to calculate the baseline. Generate a 121-dimensional onehot vector randomly, and then use multi classification logloss to get the result. The multi-class logarithmic loss value is 34.2371.

## 5 Outcome

I participated in an inactive with late submission competition. In the public leaderboard, our score is 4.41216; I rank 746 among the 1049 teams. In the private leaderboard, our score is 4.41558; I rank 778 among the 1049 teams. My ranking is not displayed directly on leaderborad because of late submission. So I got the ranking based on the historical leaderboard. The screenshots are in Figure 4.

## References

- [1] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.