

Side Scan Sonar Image Classification Using Convolutional Neural Networks

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1 Introduction

Side Scan Sonar Images are images which are generated by Side Scan Sonar sensors. These sensors are widely used for mapping of seabed, creating natural charts and so on. Enabling a system which is capable of detecting or classifying the object in Side Scan Sonar images will help in marine archaeology and defence field. Our system rectifies the deficiency of Side Scan Sonar images by creating a dataset by transfer learning, which is fed into a Convolutional Neural Network model for classification.

2 Abstract

The proposed system consists of two parts, one for data set generation and the other for classifying task. We have used transfer learning methodology for creating a data set that contains images similiar to real sss images from normal optical images which is less expensive and less time consuming.

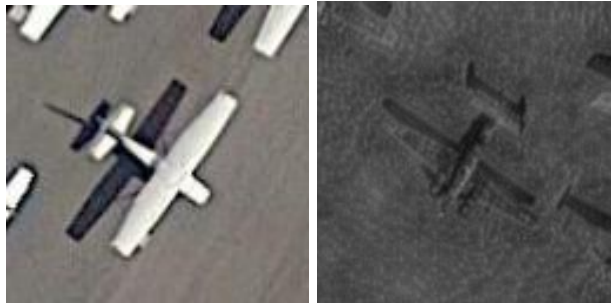


Figure 1: Content Image and Generated Pseudo Image

Once the data set is generated, it is used for training the CNN model with a set of 6178 files belonging to 3 classes and the model is validated using a validation data set of 2646 files belonging to 3 classes.

3 Methodology

Style transfer method is used here for generating SSS images. The normal optical images of 3 classes are collected (Airplanes, Ships and other images). The style of original SSS images are extracted and applied over the content of the optical images which we have collected earlier. Thus the pseudo images of SSS images are created. PhotoWCT is used for embedding features transformation. This will extract the features and reconstruct the image without losing any features followed by up-sampling and max-pooling methods so that the main features will not be lost. To erase the checkerboard effect for larger images we have added a small amount of noise in pixels where the values are 0.

Images which are generated by the above method are then fed into CNN. We have used a convolutional layer of 24 filters and the activation function, relu. Then we have max-pooled the images with 4 by 4 size and flattened it. This is followed by two dense layers which marks as the classification layer. Sparse-Categorical-Crossentropy is used as the loss function.

We got 67 percentage of accuracy for validation. Till 10 epochs the model showed increase in validation accuracy and decrease in loss function, further increment in number of epochs started to give a negative impact on validation accuracy.

4 Result

The system is able to classify the objects into required classes. The system will give a list of values for three classes. The image we want to classify belongs to the class which corresponds to the largest value

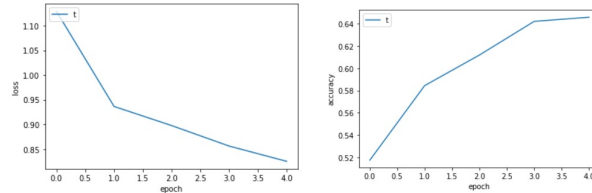


Figure 2: Loss function And Accuracy Score

among the list and also it will show the name of the class to which the test image belongs.

```
In [10]: test_image, test_image_array = preprocess_image(test_image)
         print(test_image_array)
         test_image_array.shape
         test_image_array.dtype
         test_image_array

Out[10]:
array([[ 0.0,  0.0,  0.0, ...,  0.0,  0.0,  0.0],
       [ 0.0,  0.0,  0.0, ...,  0.0,  0.0,  0.0],
       [ 0.0,  0.0,  0.0, ...,  0.0,  0.0,  0.0], ...,
       [ 0.0,  0.0,  0.0, ...,  0.0,  0.0,  0.0],
       [ 0.0,  0.0,  0.0, ...,  0.0,  0.0,  0.0],
       [ 0.0,  0.0,  0.0, ...,  0.0,  0.0,  0.0]])
array('float64')

In [11]: print("The image belongs to {}".format(class_names[test_image_array.argmax()]))
         print("Image used for prediction is {}".format(test_image))
         print("Image belongs to {}".format(class_names[test_image_array.argmax()]))

Out[11]:
The image belongs to 3 (airplane) class
Image used for prediction is 3 (airplane)
```



Figure 3: Snapshot Of Output