Transfer Learning and Data Augmentation for Semantic Ship Defect Segmentation

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Introduction

- The United Nations Conference on Trade and Development (UNCTAD) [1] reports that the 80% of the volume of international trade in goods is carried by sea.
- Being able to repair ships does not only reduce economic losses, but it can also prevent catastrophic accidents and pollution of the marine environment
- The main goal of this work is to automate the detection of damage to the hull of ships. Transfer learning and Data augmentations will be used to attempt to improve model performance.

Materials and Methods

- We combined two existing datasets varying proportions of each dataset resulting in 5 different ones.
- Albumentations [4] is the library utilized in the case presented. It provides a single interface for working with various computer vision tasks like classification, semantic segmentation and instance segmentation.
- The initial architecture of U-Net used has 64 start filters, 5 depth layers, and a latent vector of size 1024.

Abstract

The inspection of shipboard structures by people is a time-consuming and expensive activity, creating the need to search for better solutions. Simultaneously, there is a growing desire for more comprehensive and intensive data collection in order to provide a better foundation for refined condition evaluation. As the implementation of segmentation (AI) on common problems becomes more realistic. In this research, we studied how transfer learning and data augmentation work in the segmentation of defects. U-Net models aimed at segmenting ship damage are trained using five data sets in total. This research shows that transfer learning can be effective when there is little data in the original dataset. It would be of interest to see if Few-Shot learning can be used to improve the precision of segmentation.

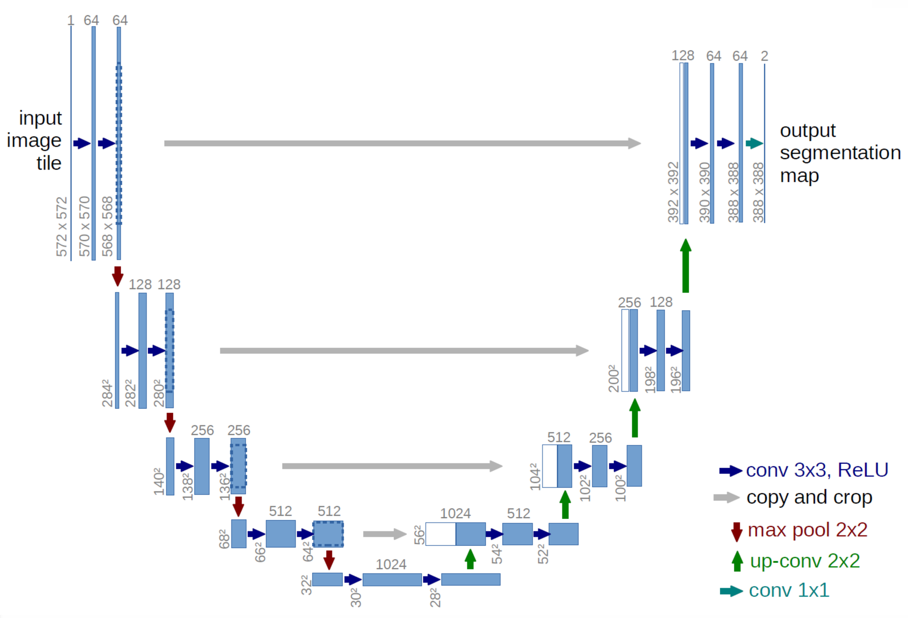

Figure 1. U-Net Architecture The reason for using that model is because we need to convert feature maps into a vector but also reconstruct an image from this vector. This is a huge task because it is much tougher to convert a vector into an image than vice versa. The whole idea of U-Net is to solve this problem.

Materials and Methods

Figure 2. The Ship Defects dataset [2] contains breaks in a metal surface and hull rust images. Each image has different sizes between 2359px x 1582px and 674px x 446px. The images have different resolutions but all of them are RGB images.

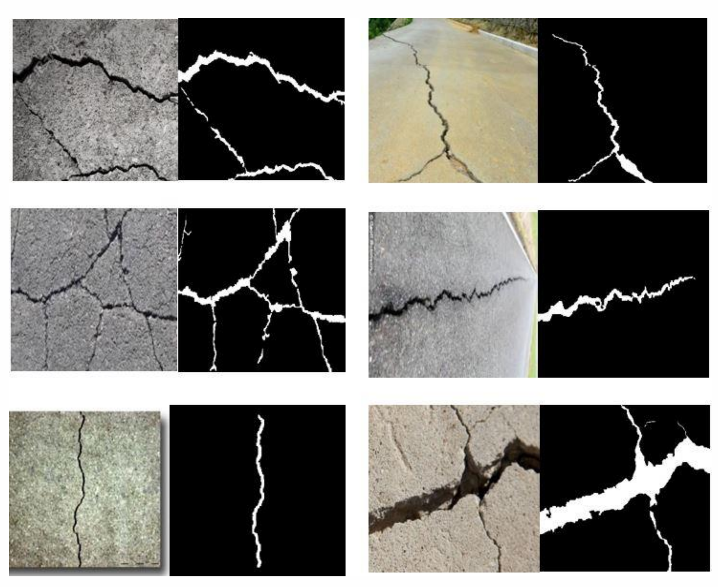

Figure 3. The Concrete Break dataset [4] contains concrete images split in 44 for training and 15 for the validation. There is a substantial difference between the type of damages from this dataset But the main purpose of using this dataset is because the rust in a metal surface can turn to a break or similar.

NAME	PROPORTIONS		TRAINING		VALIDATION		TEST	
	Ship Defects	Concrete breaks	Ship Defects	Concrete breaks	Ship Defects	Concrete breaks	Ship Defects	Concrete breaks
Ship Defects	100%	0%	50	0	13	0	10	0
MixedDataset1	50%	50%	40	40	15	15	10	0
MixedDataset2	67%	33%	40	20	15	8	10	0
MixedDataset3	33%	67%	20	40	8	15	10	0
Concrete Breaks	0%	100%	0	44	0	15	10	0

Table 1. Proportions of the Used Datasets. The idea is to get a balanced base where the model can learn all the types of damages. It has to be noted that each kind of image has a different type of annotation, the crack images have a much precise annotation than the Ship defects annotation.

Experiments and Results

Several experiments were run on the various datasets. They can be divided in the following categories; regular supervised image segmentation, transfer learning, and the previous options with data augmentations:

- To improve the performance of the regular experimentation, transfer learning was implemented on the training and validation.
- The model contains 20 parameters of which 8 are the more suitable to modify.
- To study the performance of the model in different environments, 3 different data augmentations (DA) were applied: Grayscaling, RandomContrast and Rotation.

Experiments and Results

Datasets	F1-Score	IoU	Precision	Recall
TODDIS Defects	0.1785	0.0995	0.5145	0.1345
MixedDataset1	0.0868	0.046	0.2635	0.0555
MixedDataset2	0.192	0.137	0.4	0.172
MixedDataset3	0.246	0.14	0.386	0.282
Concrete Breaks	0.142	0.076	0.295	0.921

Table 2. Transfer Learning results: This table shows the results of the baseline results: these experiments were run with standard parameters and without data augmentation.

- The results show that, with the increase of Concrete Breaks in the used data, the recall increases.
- With the same increase in Concrete Breaks, the precision decreases.
- In figure 4, the images on the left are high precision, low recall. The images on the right are low precision high recall.
- For the purposes of this project, the priority lies with recall. We want to detect damage. Precision of the detection can be worked in in future.
- Data augmentation produced similar or worse results.

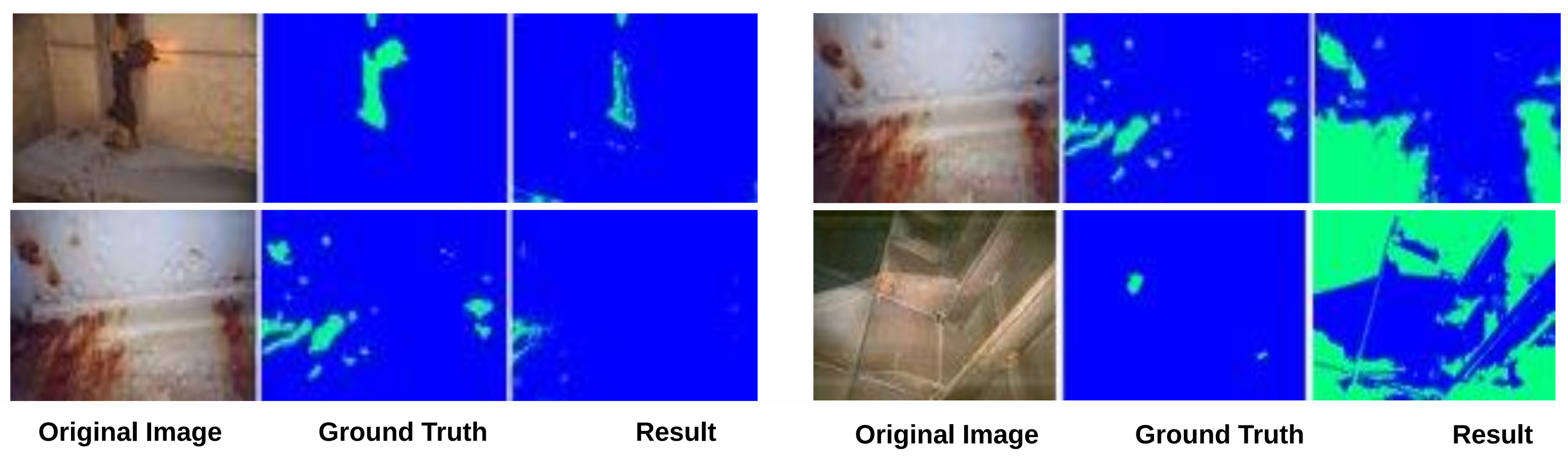

Figure 4. Transfer Learning Results. We realized that the transfer learning used improves the recall in exchange for a decrease in precision. The results of these experiments show that using the right dataset combination can improve or stabilize the values of recall, precision, and F1-score (respectively 0,189–0,2815–0,246).

DA	F1-Score	IoU	Precision	Recall
None	0.246	0.14	0.386	0.282
Gray Scaling	0,111	0,059	0,059	0.866
Random Contrast	0.114	0.063	0.119	0.113
Rotation	0.145	0.08	0.179	0.147

Table 3. Data Augmentations results: This table shows the results of applying the DA to the third mixed Dataset. The obtained results demonstrate that in most part of the cases the model learns better without DA.

Conclusions

- Through transfer learning, recall can be increased at cost of lower precision.
- The varying parameters and data augmentations lead to either similar or worse results.
- Considering the last results of the experiments in table 2, with a recall above 90%, it detects most damage in all images.
- The low precision and visual results show a lot of misclassification of background as damage.
- An Artificial Neural Network based semantic segmentation model can be used to segment damage on ships. There is, however, more to be done before it can be put to practical use.

NHL STENDEN

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