Ship corrosion detection

Applications of Deep Learning for Ship Corrosion Detection | and an optimization experimentation tool

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Introduction

- Ships get corroded/damaged by harsh sea conditions.
- Ships have to be maintained accordingly which includes a semi regular inspection.
- These thorough inspections are repetitive, labour intensive, inspectors must fly across the world to perform the inspections and they end up being financially costly.
- The first goal of this project is to optimize the inspection process using a deep learning model.
- The second goal of this project is to create an automatic experimentation tool which can help with optimizing deep learning models.

Materials and Methods

- The MaVeCoDD[1] dataset contains 79 different images of ship hulls.
- The dataset was already annotated, and they were split in a high-resolution and low-resolution directory.
- The U-Net[2] deep learning architecture.

Abstract

Optimizing the visual inspection of ship conditions. The goal was to speed up ship inspections with the help of a U-Net deep learning model. This model was improved with an optimization experimentation tool. The model was accurate in detecting regions of rust and very accurate at detecting the background.

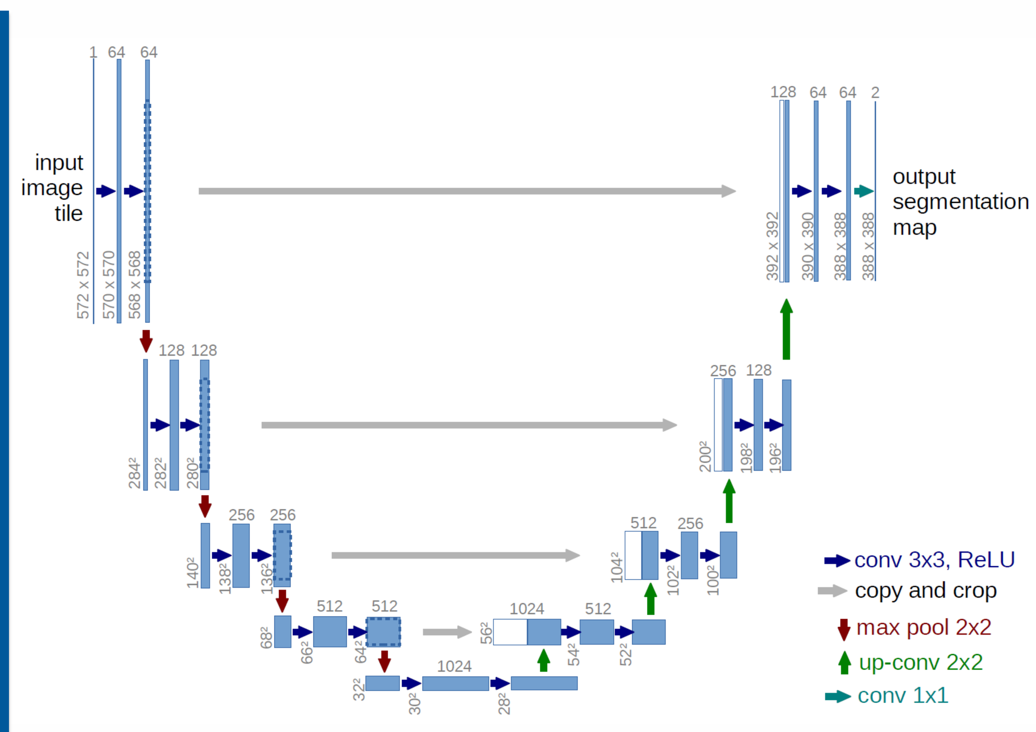

Figure 1. The U-Net^2 architecture

Materials and Methods

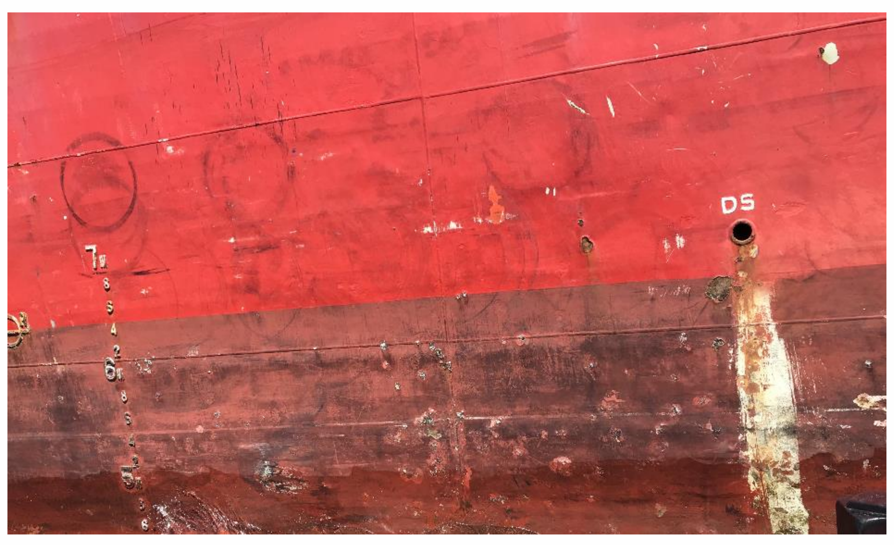

Figure 2. Raw image from the MaVeCoDD dataset

Figure 3. Annotated image from the MaVeCoDD dataset.

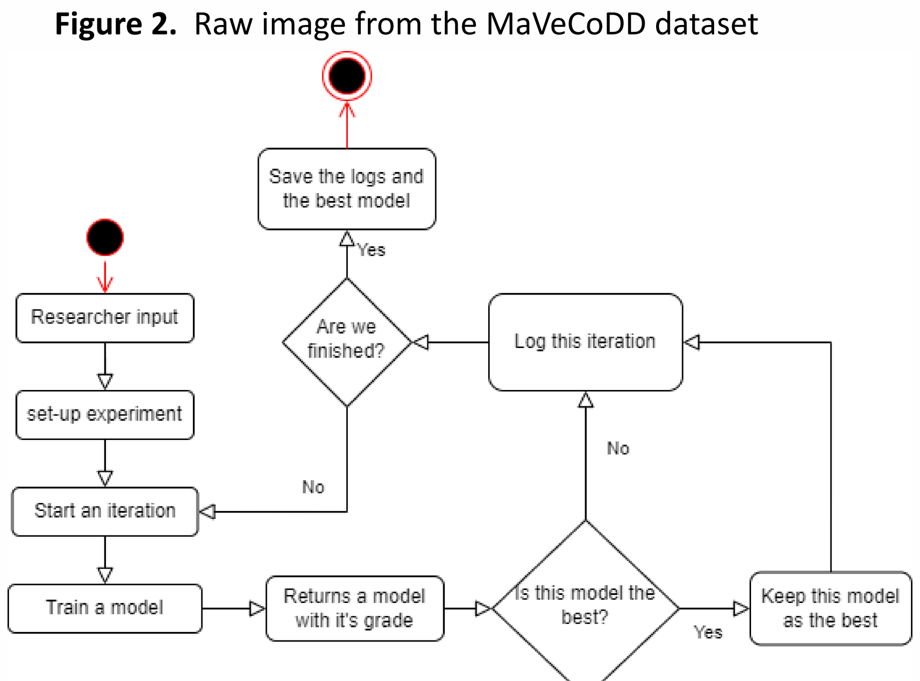

Figure 4. Flowchart of the automatic experimentation tool

- The optimization experimentation tool was created in python.
- It is a dynamic tool which can be used in different environments.
- The tool was created with practicality in mind and is therefore easy to use.

Experiments and Results

Segmentation of rust

The model is segmenting rust from ship hull images. It can accurately detect the presence of rust and has little False Positives. There is however a bit of noise in the middle of the rust patches. This can be seen in the number of False Negatives and the sensitivity. The data in the confusion matrix was generated based on the pixels of the segmented results.

True class

Predicted class	Positive	Negative
Positive	1,994,987	168,310
Negative	902,183	6,109,560

Accuracy of 0.8833

Table 1. The confusion matrix generated from the test dataset. Which consisted of 4 images which were not used during the training process.

Metric	Score
Sensitivity	0.6686
Specificity	0.9732
Precision	0.9222
F_1-score	0.7885

Table 2. The sensitivity, specificity, precision and f_1-score generated from the confusion matrix.

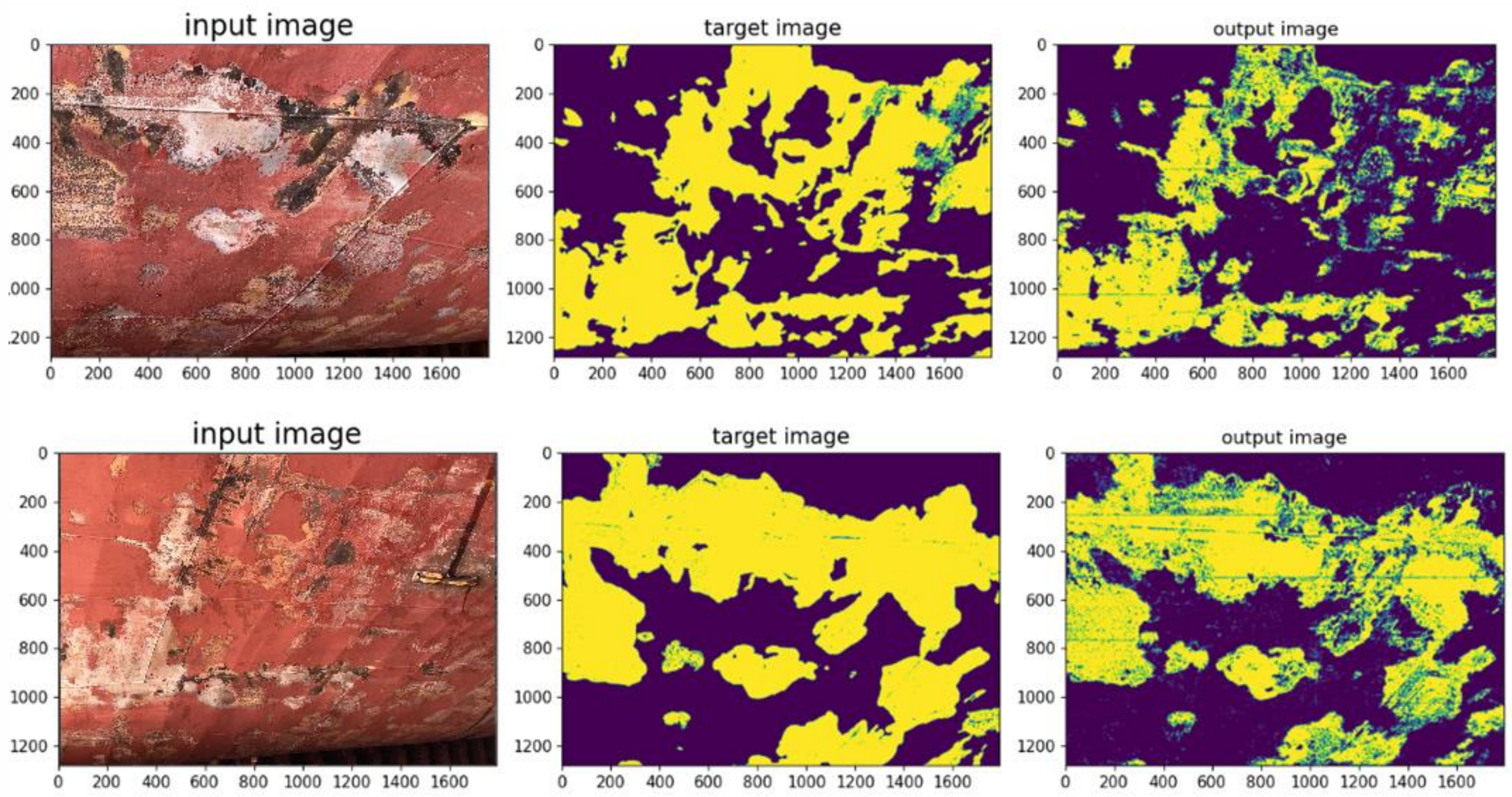

Figure 5. Results from the models. The input image is the original image which was used as the input of the model. The target image is an annotation in which all the rust has been annotated. And the output image is the output of the model.

Optimization experimentation tool

The model used to create the results was optimized using the experimentation tool. The model's hyperparameters were optimized during experimentation. The tool was also tested by fellow student. The test was done within their project which included a different python environment, dataset and deep learning model.

Conclusions

- U-Net can segment rust from images of ship hulls.
- These segmentations are accurate in detecting the background. It can also detect the contours of the rust regions but has trouble completely filling these regions.
- This could be fixed with longer training times, a more diverse dataset or with a flood fill.
- The tool was tested by a student, who noted that the tool was easy to use and they would've wanted to use it for their experiments.
- The tool is under evaluation by the professorship and future functionalities are already in development.

Acknowledgements

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SIA Regieorgaan

References

[1]Chliveros, Georgios; Tzanetatos, Iason; Kamzelis, Konstantinos (2021), "MaVeCoDD Dataset: Marine Vessel Hull Corrosion in Dry-Dock Images", Mendeley Data, V1, doi: 10.17632/ry392rp8cj.1

[2]Olaf Ronneberger, Philipp Fischer and Thomas Brox (2015), "U-Net: Convolutional Networks for Biomedical Image Segmentation", doi: 10.1007/978-3-319-24574-4_28