AUTOMATED IMAGE ANALYSIS

FOR IDENTIFYING BIOFOULING RISK OF VESSELS

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cebra
Centre of Excellence for Biosecurity Risk Analysis

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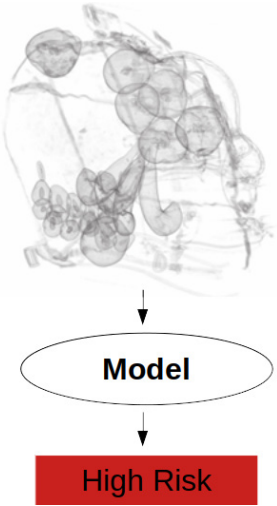
- This means that...
  - if 1 million containers are imported, we will have 1000 leakage events.
  - if 2 million containers are imported, there will be 2000 leakage events.
- As volumes increase, higher levels of intervention are required maintain current levels of risk.

Machine Learning can help

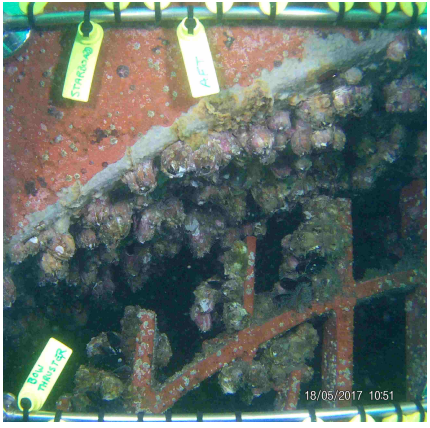
- Machine learning aims to develop computational models that can solve time-consuming and repetitive tasks.
- Given an input (passenger information, image, document, video, text, etc.) a machine learning model can support or automate decision making.



[1]Image taken from DAWE's Innovative Biosecurity 3D X-ray Project

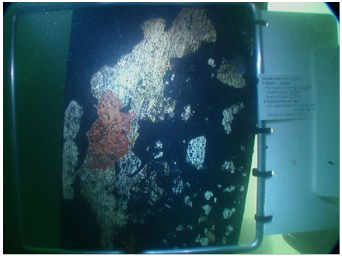
Machine Learning problems are everywhere in biosecurity

- Does an X-ray image contain a potential biosecurity risk?
- Given what we know about a particular passenger or cargo consignment, are they likely to be carrying biosecurity risks?
- Are the documents provided with a consignment fraudulent?
- **Does the biofouling on this vessel pose a biosecurity risk?**

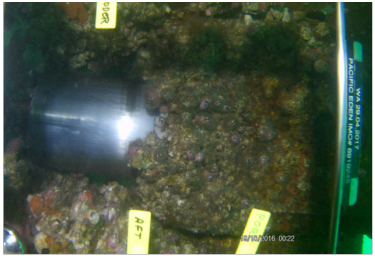


The Project

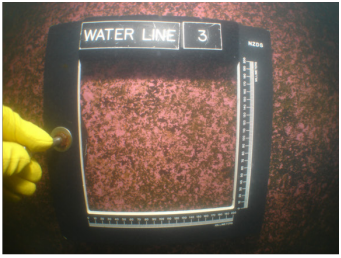
Can we develop a method to assist/automate the assessment of images and footage for biofouling?



Level of fouling X?



Level of fouling Y?



Level of fouling Z?

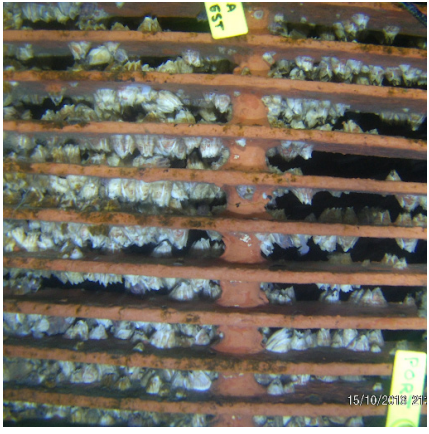
The Project: Use Cases

Building a machine learning model

1. What is the decision that I need the computer to make?
2. What data could be used to train the model?
3. Does my model perform well enough?

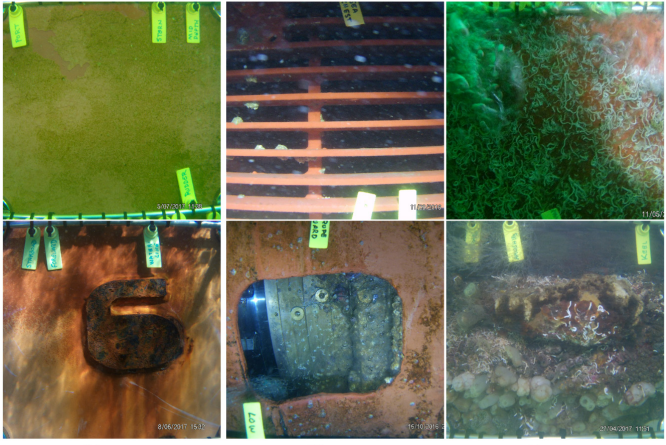
1. What is the decision that I need the computer to make?

- Biosecurity regulators care about the overall state of the vessel
  - Overall, how severe is fouling on the vessel?
  - Are particular areas badly fouled (e.g. sea chests)
  - Are there species of concern?
- These high level questions are challenging!



Defining a labelling scheme

An **easier** question: In an image, what is the degree of fouling present?



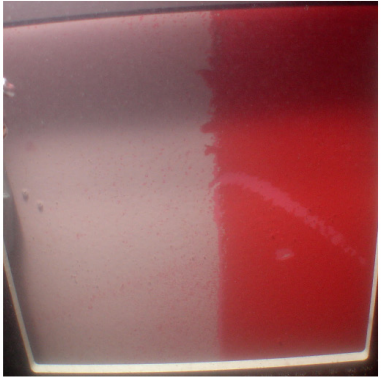
(a) SLoF 0 **(b)** SLoF 1 **(c)** SLoF 2

The data-labelling process

Click here to show examples

Select the most appropriate box for the image

Image can be zoomed with mousewheel and panned by clicking and dragging.



What fouling description best reflects this image? (hotkeys are 1, 2 and 3)

No fouling organisms, but biofilm or slime **MAY** be present.

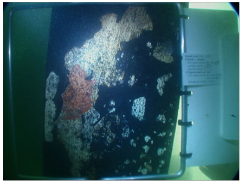
Fouling organisms (e.g. barnacles, mussels, seaweed, tubeworms, etc.) are visible but patchy (1-15% of surface covered).

A large number of fouling organisms are present (16-100% of surface covered).

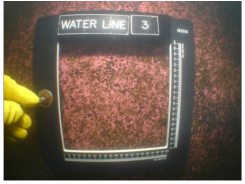
Submit (hotkey enter)

2. What data could be used to train the model?

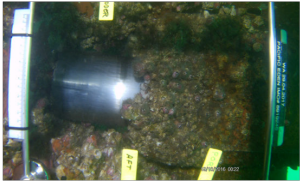
- Obtained over 10,000 images from NZ MPI, the Australian DAWE and California's SLC.
- Around 300 vessels represented including commercial, recreational and barge vessels.
- Dataset was highly imbalanced! Around 70% of images were clean, 20% lightly fouled, and 10% heavily fouled.



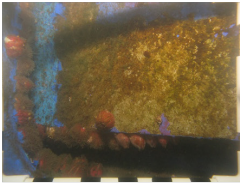
NZ Recreational



NZ Commercial

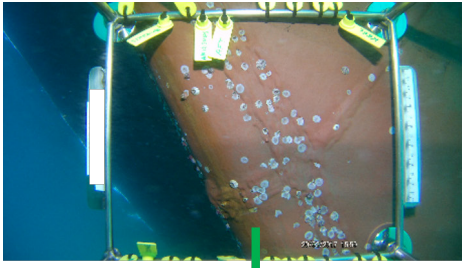


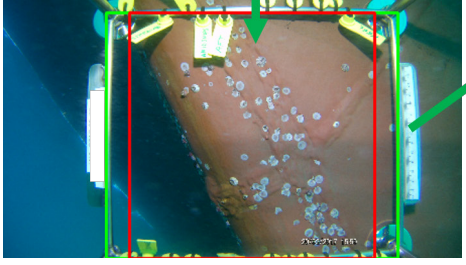
DAWE

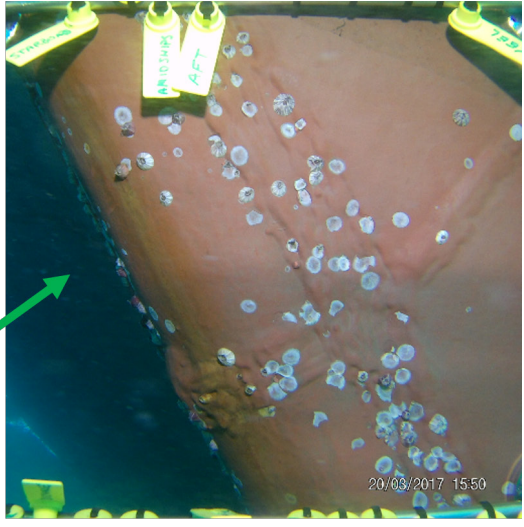


California SLC

Processing the data

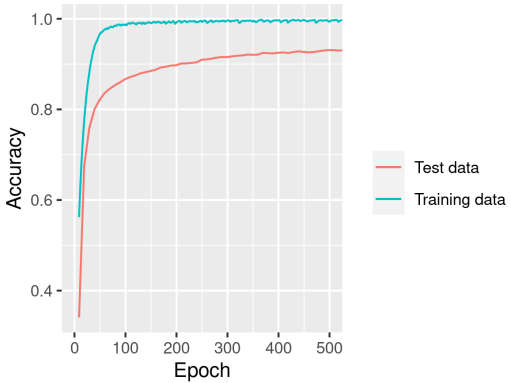






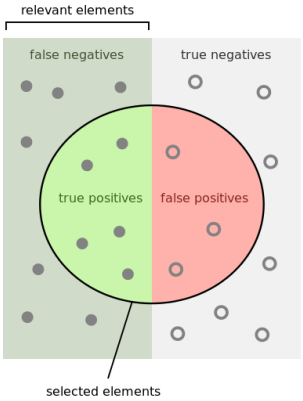
Training the models

1. Split the data into a **training** and a **test** set.
2. Optimise the model on the **training** set.
3. Evaluate model performance on the with-held **test** data.



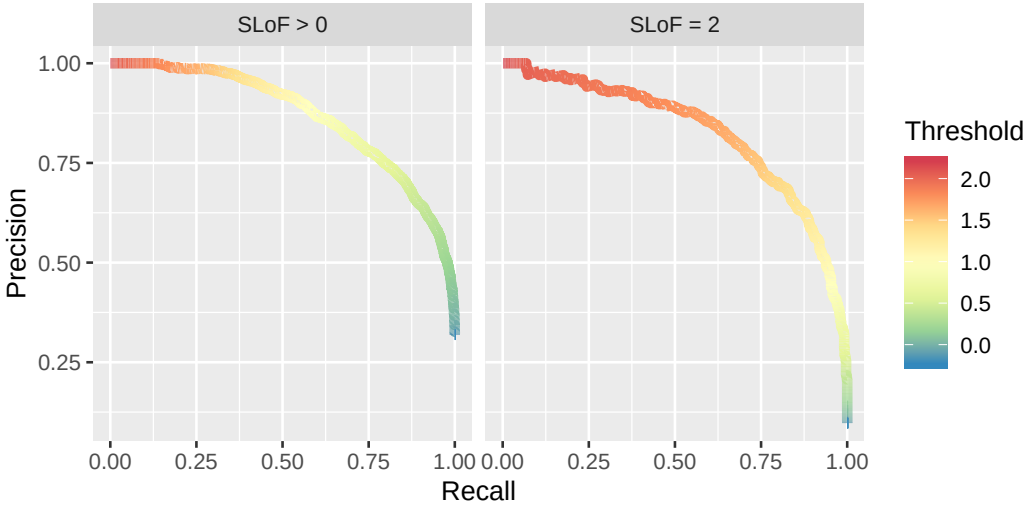
3. Does the model perform well enough?

- **Accuracy** — proportion of images correctly identified.
- **Recall** — proportion of images with a biosecurity risk that we correctly identify (true positives versus false negatives)
- **Precision** — proportion of flagged images that actually have a biosecurity risk (true positives versus false positives)
- As model output is a raw number (e.g. 0.45) we need to define thresholds to obtain predicted classes before we can calculate precision and recall!

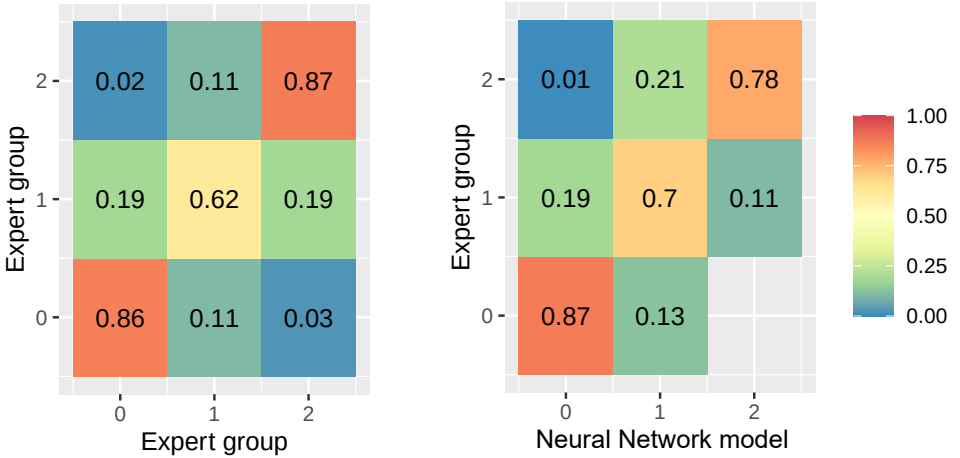


Accuracy = 12/22
Precision = 5/8
Recall = 5/12

Model criteria: precision-recall curve



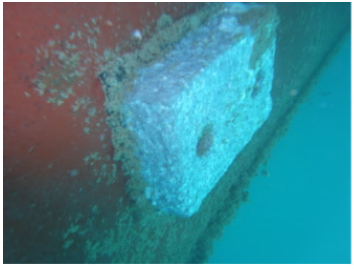
Comparing the neural network model to expert agreement



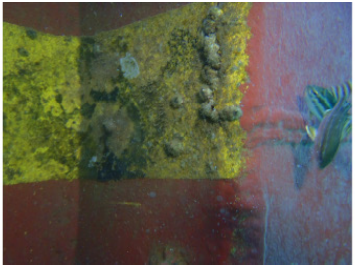
Bloomfield, N. J., Wei, S., Woodham, B. A., Wilkinson, P., & Robinson, A. P. (2021). Automating the assessment of biofouling in images using expert agreement as a gold standard. Scientific reports, 11(1), 1-10.

Apply the model to real-world data

SLoF 0



SLoF 1



SLoF 0

Next steps

- A multi-year CEBRA project is currently ongoing to further develop and support the operationalization this work. The key objectives include:
  - Expanding the image dataset to include examples from commercial vessel surveys
  - Develop cost-effective strategies for labelling and incorporating new data
  - Extend the approach to video data
  - Integrating the neural network models with a prototype user interface

Acknowledgments

- Thanks to Ramboll New Zealand for providing experts to classify our test set of images and the Mechanical Turk workers that contributed to the project.
- Thanks to Daniel Kluza from the New Zealand Ministry of Primary Industries for providing their biofouling dataset.
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