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Image-based beach state classification using convolutional neural networks

Introduction

- Unravelling the dynamics of subtidal sandbars is crucial to the understanding of nearshore sediment pathways.
- Wright and Short (1984) created a beach state classification scheme in which they distinguish a total of six beach states with distinct sandbar configurations.
- The tremendous progress in data-driven learning in image recognition has led to a first automated classification of single-barred beach states from video (Argus) imagery using a Convolutional Neural Network (CNN) (Ellenson et al., 2020).

Goal

- Our goal was to create a model for the automated classification of double-barred beach states.

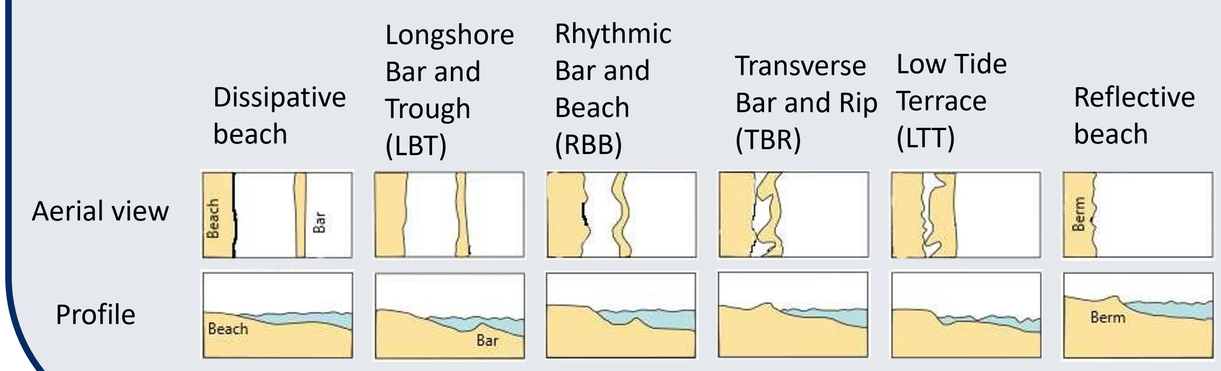


Figure 1. Beach states as created by Wright and Short (1984).

Datasets

- Labelled Argus imagery of the single-barred beaches of Duck (US) and Narrabeen (Australia) and the double-barred beach of the Gold Coast (Australia).

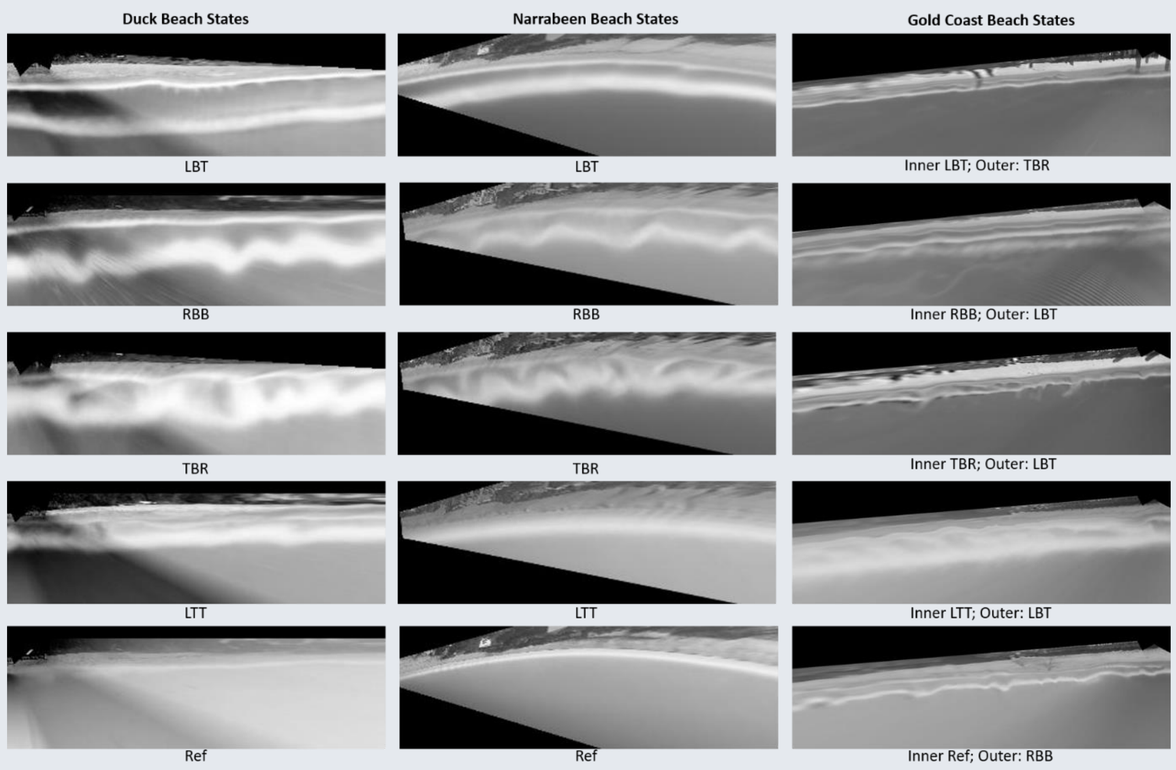


Figure 2. Examples of Argus images from each location (l.t.r. Duck, Narrabeen and Gold Coast).

Pre-processing

- Normalized in range [0,1]
- Resized to 224x224 pixels
- Sorted by time
- Distributed in train (80%), validation (10%) and test (10%) sets
- Weights
- Augmentations

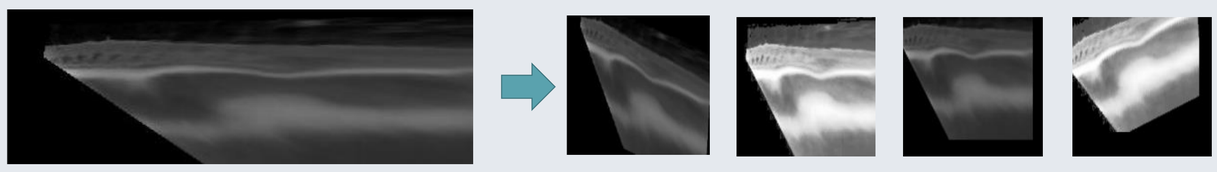
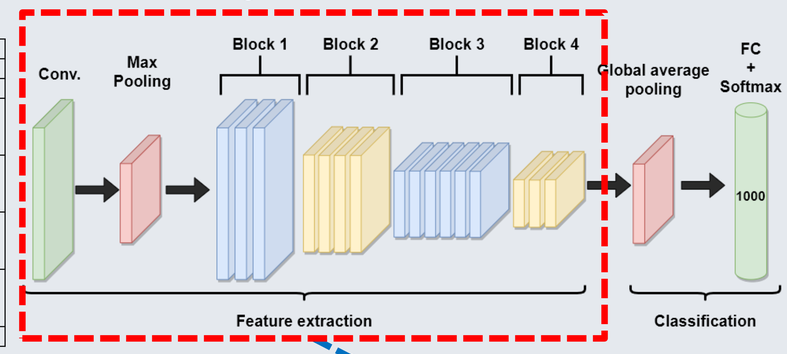


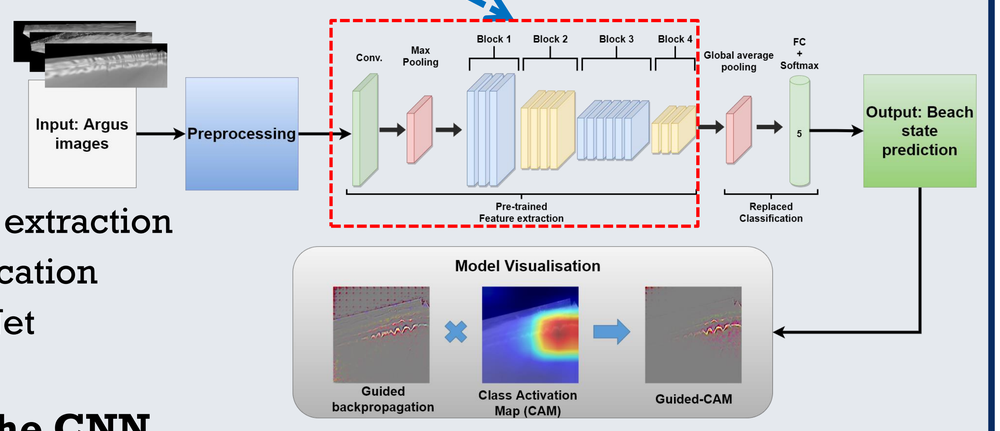
Figure 3. Example of image being resized and with different augmentations applied.

Convolutional Neural Network and Transfer learning

Figure 4. ResNet50 architecture, transfer learning and model visualisation.

Layer name	Output size	50-layer
Conv.	112x112	7x7, 64, stride 2
Block 1	56x56	3x3 max pool, stride 2
		$\begin{bmatrix} 1x1, 64 \\ 3x3, 64 \\ 1x1, 256 \end{bmatrix}$ x 3
Block 2	28x28	$\begin{bmatrix} 1x1, 128 \\ 3x3, 128 \\ 1x1, 512 \end{bmatrix}$ x 4
Block 3	14x14	$\begin{bmatrix} 1x1, 256 \\ 3x3, 256 \\ 1x1, 1024 \end{bmatrix}$ x 6
Block 4	7x7	$\begin{bmatrix} 1x1, 512 \\ 3x3, 512 \\ 1x1, 2048 \end{bmatrix}$ x 3
	1x1	Average pool, 1000-d fc, softmax





- ResNet50
  - Feature extraction
  - Classification
  - ImageNet

Training the CNN

- Trained using transfer learning.
- Fine-tuning:
  - All trainable parameters are updated in the feature extraction part.
  - The classification part is replaced to match the amount of classes.

Results

Final Results: Trained only with single-barred beach data:

- The optimal classification achieved an average weighted F1 score of 0.80.
- Failed to classify double-barred beach imagery.

Final Results: Trained with both single-barred and double barred beach data:

- The optimal classification on the inner bar achieved an average weighted F1 score of 0.68.
- The optimal classification on the outer bar achieved an average weighted F1 score of 0.82.

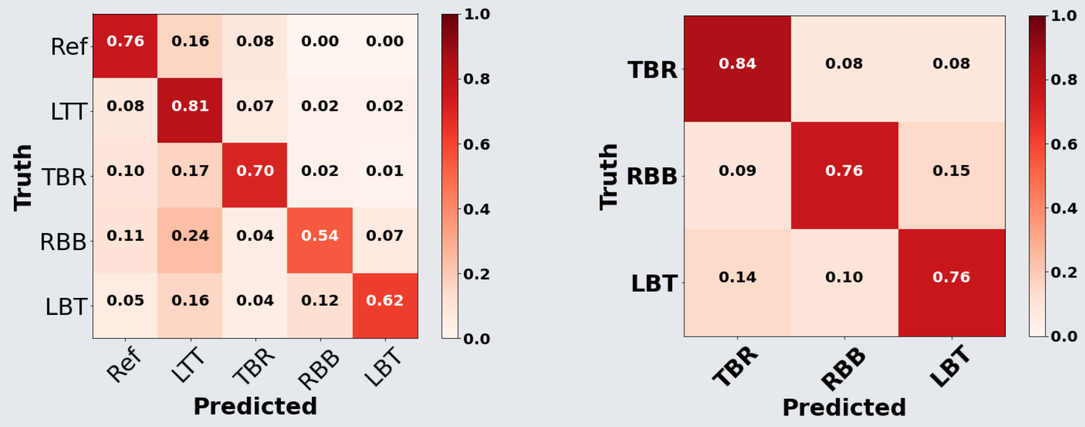


Figure 5. Per class performance on Gold Coast's inner bar (left) and outer bar (right)..

Conclusion

- **CNNs provide a promising framework for the classification of double-barred beaches.**
- **Provided the relatively small dataset, a promising accuracy was achieved.**
- **Better results could be obtained by increasing the dataset, optimizing the network parameters and using multi-label classification.**

References:
Ellenson, A.N., Simmons, J.A., Wilson, G.W., Hesser, T.J., Splinter, K.D. (2020). Beach State Recognition Using Argus Imagery and Convolutional Neural Networks. *Remote Sensing*, 12, 3953. https://doi.org/10.3390/rs12233953
Wright, L.D., Short, A.D. (1984). Morphodynamic variability of surf zones and beaches: A synthesis. *Marine Geology*, 56, 93-118, https://doi.org/10.1016/0025-3227(84)90008-2

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