Rotation Equivariant Deforestation Segmentation and Driver Classification

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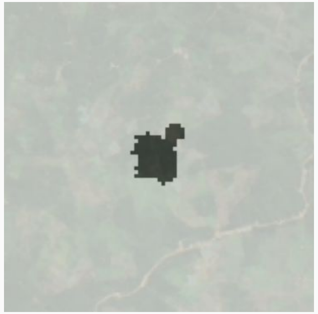
Deforestation

- Deforestation is a driver for climate change. [1]
- Tropical deforestation contributed roughly 10% of annual greenhouse gas emissions. [2]
- A quarter of of global forest loss is for commodities. [3]

[1] Global Consequences of Land Use. Science 2005
[2] Framing and Context. IPPC 2019
[3] Classifying Drivers of Global Forest Loss. Science 2018

Data

- The dataset consists of three main components [1,2].
    - Forest images.
    - Deforestation segmentation maps.
    - Deforestation driver classes.



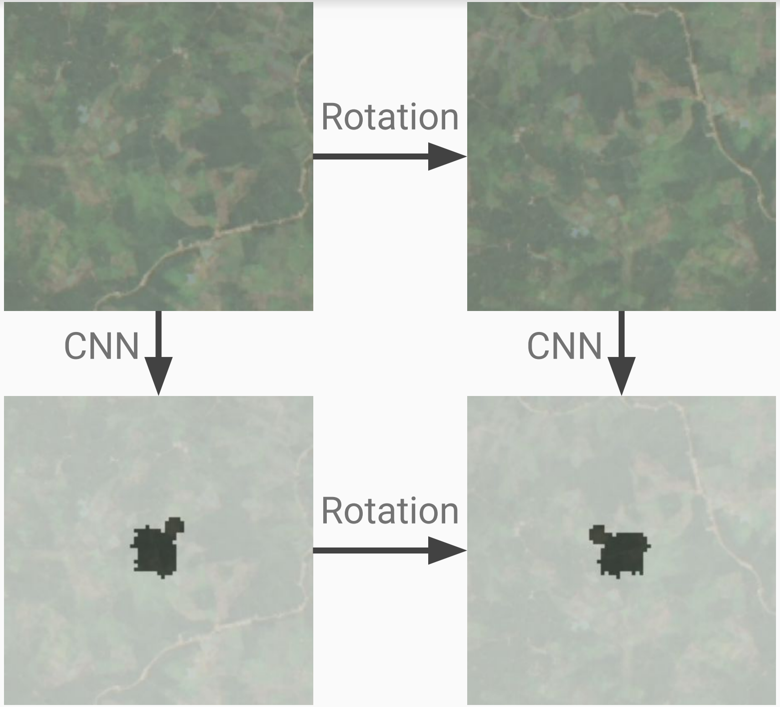
Plantation

[1] What Causes Deforestation in Indonesia? Environmental Research Letters 2019

[2] Forestnet: Classifying Drivers of Deforestation in Indonesia Using Deep Learning on Satellite Imagery. NeurIPS 2020

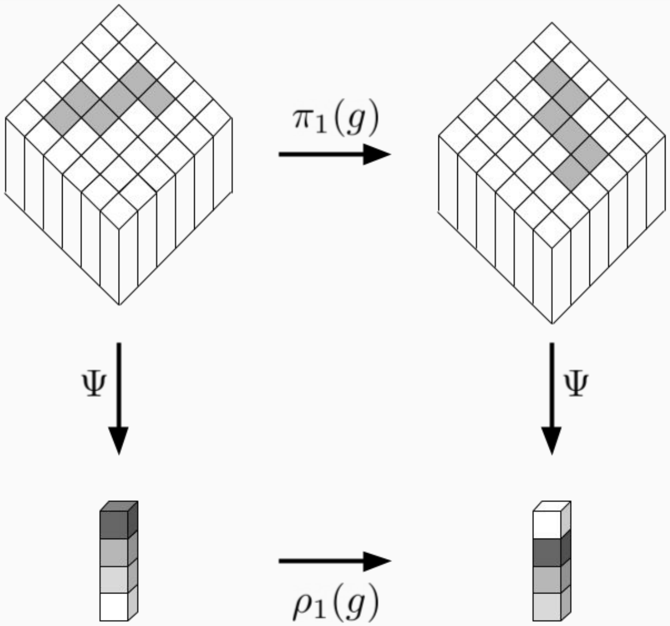
Symmetries

- A convolutional layer is translation equivariant.
  - A translated image creates a translated feature map.
- We require translation and rotation equivariance.
  - A rotated image creates a rotated feature map.
- This is a useful inductive bias for a model that makes predictions on images with rotational symmetries.



Equivariance

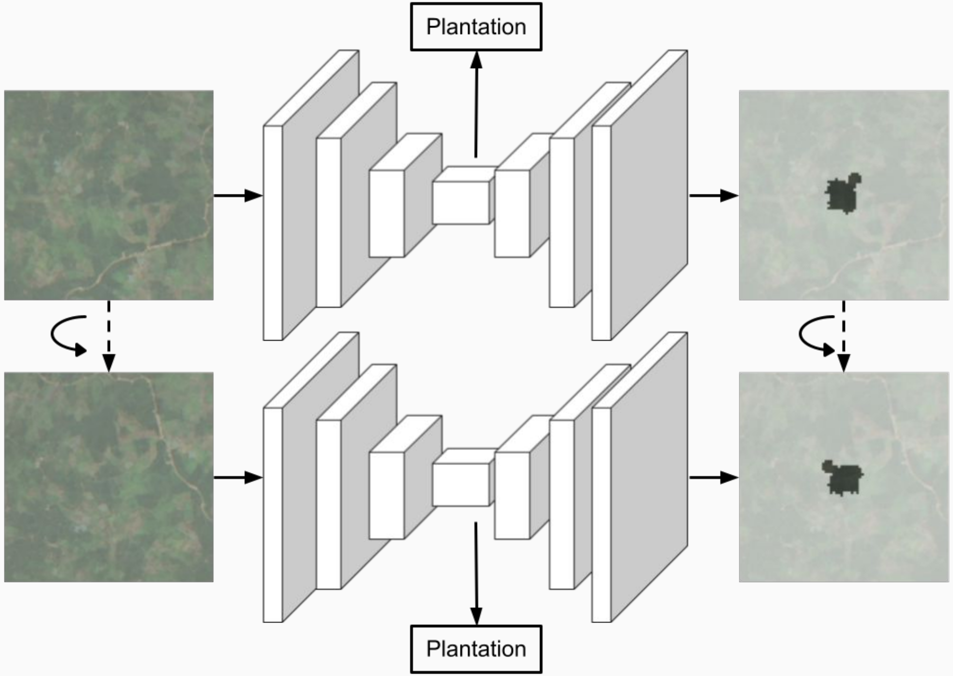
- The feature space:
  - A c-dimensional vector is linked to each point in the base space.
- The transformation law:
  - The layer is equipped with a transformation law, characterised by a group representation, which specifies how the channels of the feature vector mix under a transformation. [12]



[1] Steerable CNNs ICLR 2017
[2] General E(2)-Equivariant Steerable CNNs. NeurIPS 2019

Model

- Rotation Equivariant U-Net model.
- Stable generation of segmentation maps under rotation.
- Improved segmentation and classification accuracy.



Results

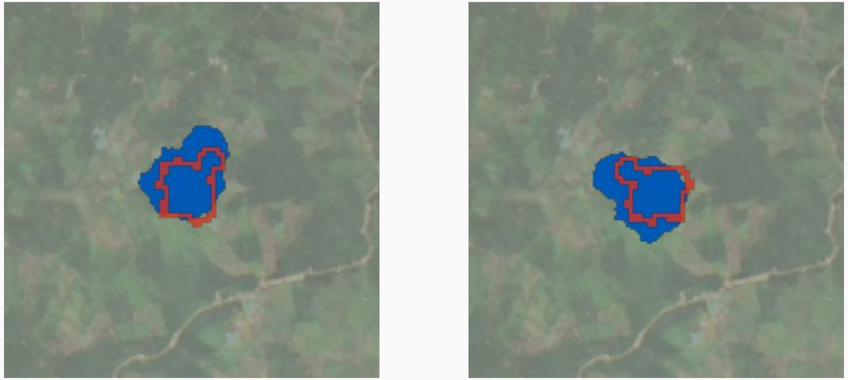
Model	Train	Validation	Test	Rotated Test
UNET - CNN	90.3	60.6	57.9	56.3
UNET - C8 Equivariant	82.7	67.1	63.0	64.3

Classification Accuracy

Model	Train	Validation	Test	Rotated Test
UNET - CNN	72.9	68.7	67.8	67.9
UNET - C8 Equivariant	84.1	71.3	72.3	72.3

Segmentation Accuracy

UNET - CNN



UNET - C8 Equivariant

Conclusion

- Improved weight sharing in the model.
- Improved segmentation accuracy by 7%
- Improved classification accuracy by 9%.
- Segmentation maps are stable under rotation.

Acknowledgements

Joshua Mitton is supported by a University of Glasgow Lord Kelvin Adam Smith Studentship. Roderick Murray-Smith acknowledges funding from the QuantIC project funded by the EPSRC Quantum Technology Programme (grant EP/MO1326X/1) and the iCAIRD project, funded by Innovate UK (project number 104690). Roderick Murray-Smith acknowledges funding support from EPSRC grant EP/R018634/1, Closed-loop Data Science.