Detection of Knots in Oak Wood Planks

Instance versus Semantic segmentation (AT22-543)

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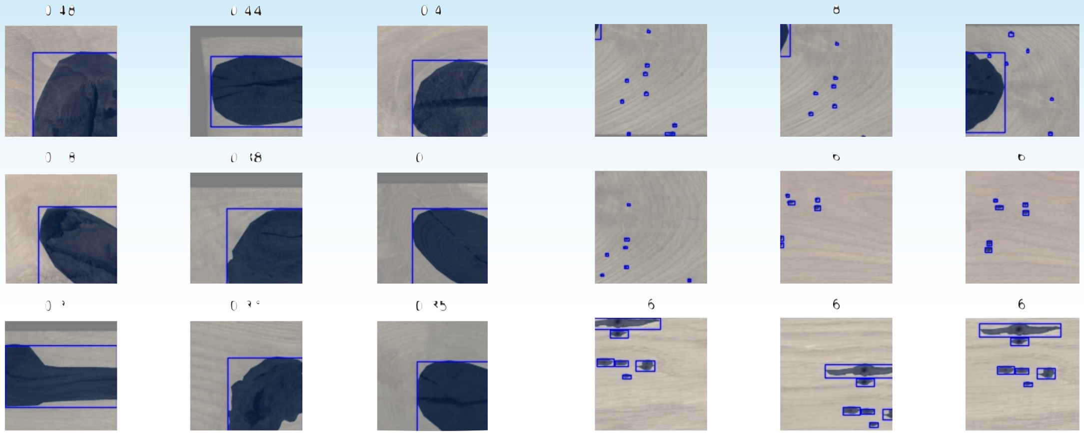
Summary

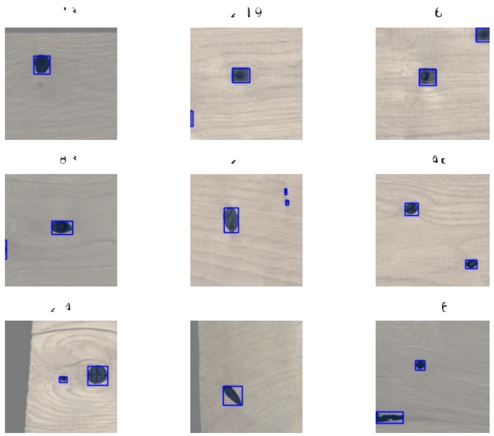
- Novel, publicly available dataset "FSCC oak knots" introduced
- Comparitve analysis between Instance and Semantic segmentation models
- Open-source implementation (https://github.com/evaldsurtans/FSCC-Oak-Knots-Dataset)

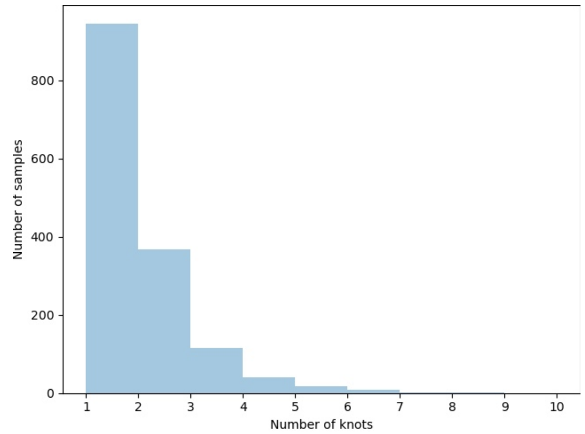
Novel Dataset

FSCC oak knots

- 1500 samples
  (1200 train, 300 test)
- 500x500 pixels RGB
- Labelled, 1 to 11 knots per image (mask & box)
- Alternatives: LSIDWS, WOOD, Wood Spieces and Kaggle Wood Textures



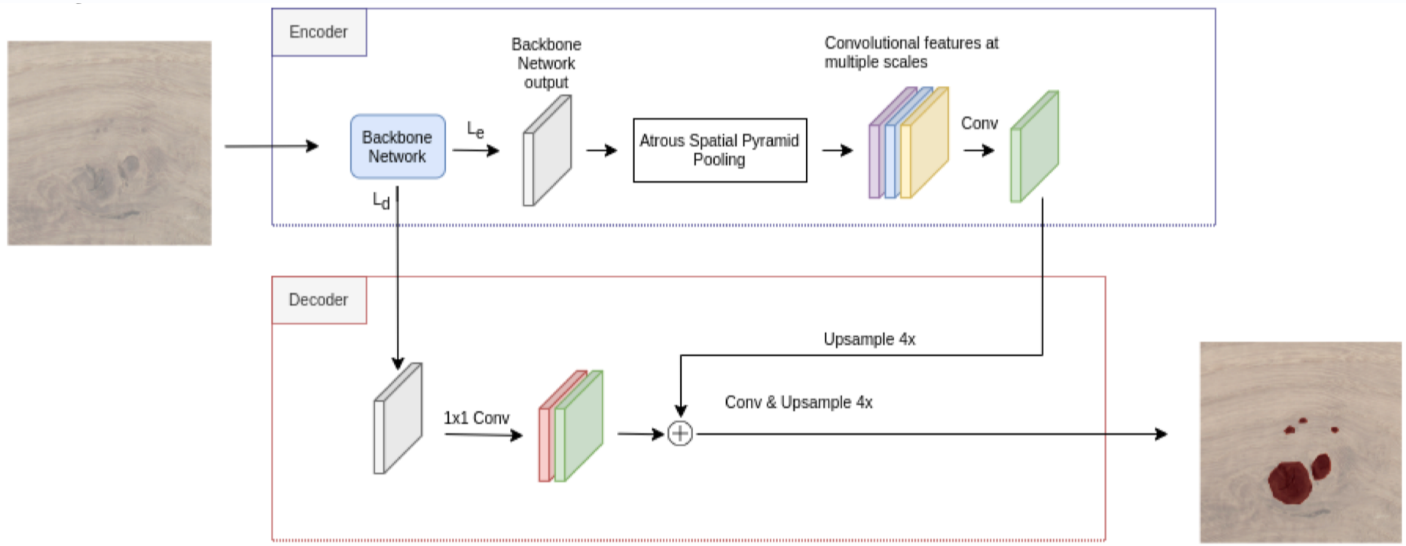




Semantic segmentation

DeepLab V3, UNet

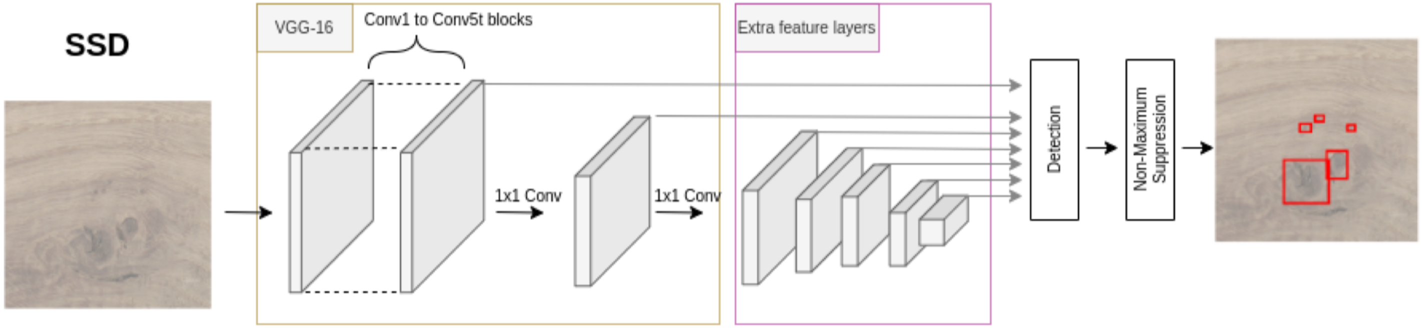
- Binary Cross-Entropy



$$\mathcal{L}_{BCE}(y, y') = -\frac{1}{N}\sum(y\ log(y' + \epsilon) + (1 - y)\ log((1 - y') + \epsilon))$$

Instance segmentation
Single-Shot Detector (SSD)

- Binary Cross-Entropy
- L1 Smooth loss
- Non Maximum Suppression algorithm



$$\mathcal{L}_{L1\ smooth} = \frac{1}{N}\sum \begin{cases} 0.5(y_n - y_n')^2/\beta, & \text{if } |y_n - y_n'| < \beta \\ |y_n - y_n'| - 0.5\beta, & \text{otherwise} \end{cases}$$

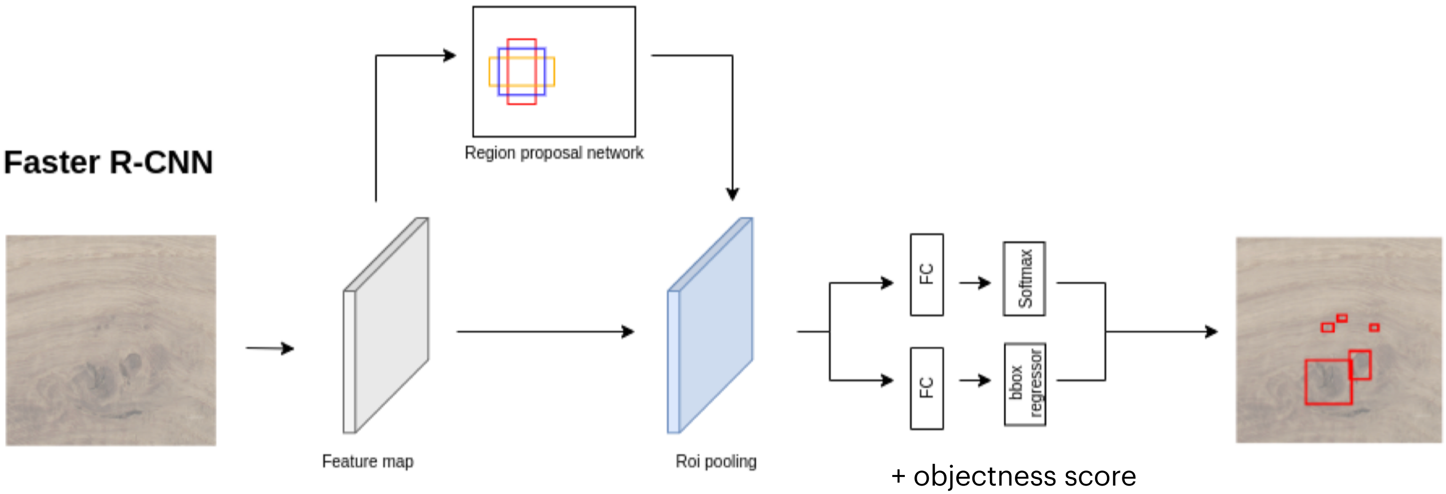
$$\mathcal{L}_{SSD} = \mathcal{L}_{L1\ smooth} + C\,\mathcal{L}_{BCE}$$

Instance segmentation

Faster Region-based Convolutional Neural Network (Faster R-CNN)

- Binary Cross-Entropy
- L1 Smooth loss
- Objectness loss
- Non Maximum Suppression algorithm

Faster R-CNN



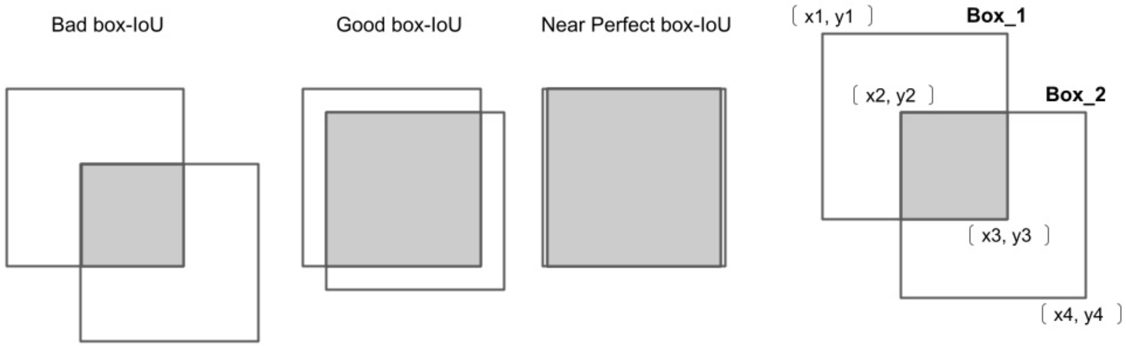
$$\mathcal{L}_{L1\ smooth} = \frac{1}{N}\sum \begin{cases} 0.5(y_n - y_n')^2/\beta, & \text{if } |y_n - y_n'| < \beta \\ |y_n - y_n'| - 0.5\beta, & \text{otherwise} \end{cases}$$

$$\mathcal{L}_{objectness} = \frac{1}{N}\sum (IoU - IoU')^2$$

$$\mathcal{L}_{RCNN} = \mathcal{L}_{L1\ smooth} + C_1\ \mathcal{L}_{BCE} + C_2\ \mathcal{L}_{objectness}$$

Metrics

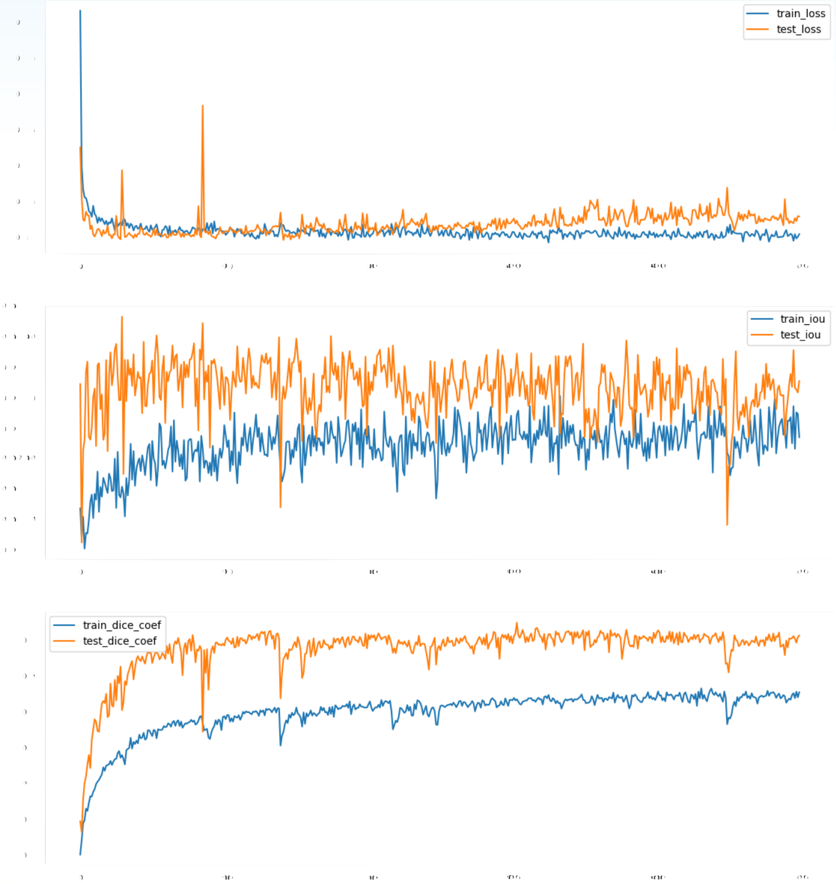
- Pixel-based IoU (Intersection over Union Jaccard index)
- Box-based IoU
- Accuracy (did it detected a kont at all in given image that contains a knot)

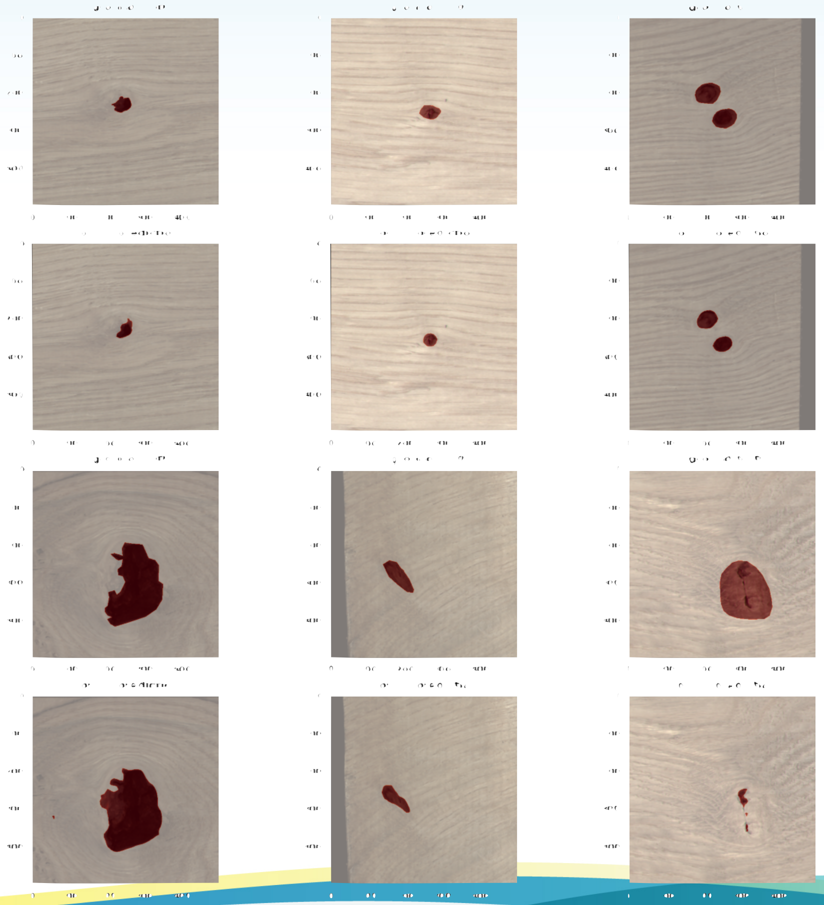


Training protocol

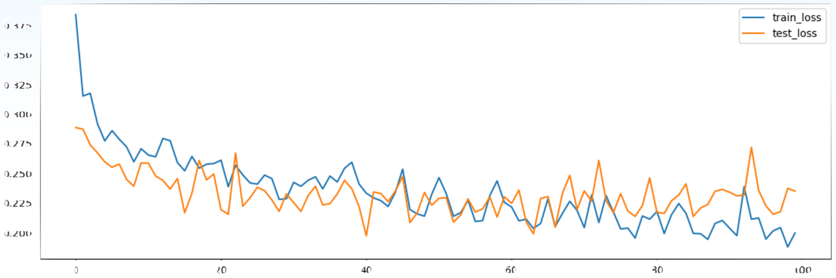
- Augmentations (horizontal flip, vertical flip, scale, rotation, and color jitter)
- Weighted Binary Cross-Entropy, based on pixel distribution
- Grid search of hyper-parameters (batch_size, learning_rate, model, confidence thresholds)

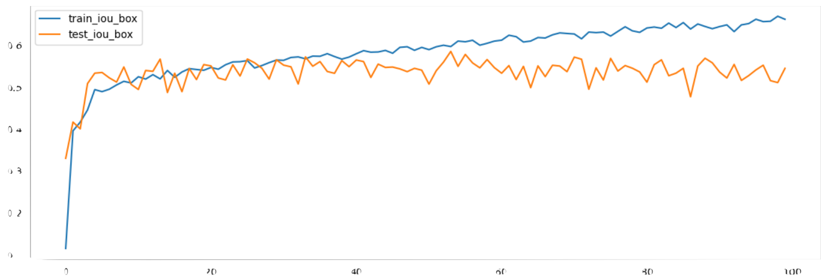
Semantic Segmentation

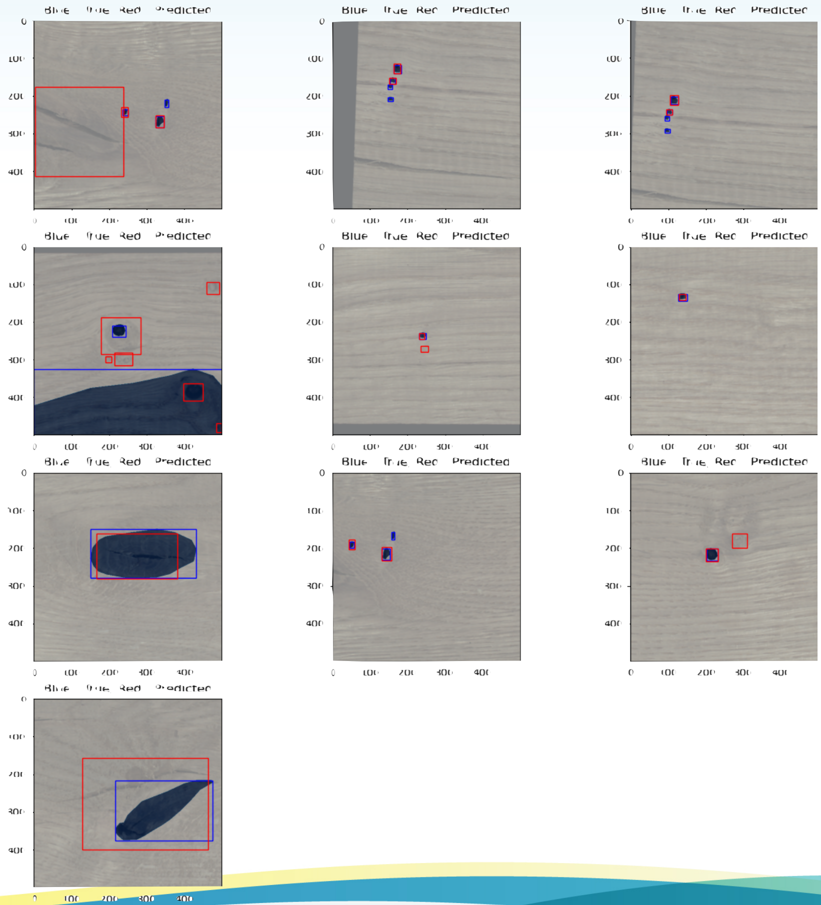




Instance Segmentation







Results
and conclusions

- Dataset is feasible for task
- Instance segmentation has superior **59% Box-IoU** and **90% acc.** versus **49% Box-IoU** and **89% acc.** using semantic segmentation
- UNet-based DeepLabV3 has superior **51% Pixel-IoU** versus **42% Pixel-IoU** using FCN

Model	Method	Pixel IoU	Box IoU	Acc.
Faster R-CNN	Instance segmentation	N/A	**0.59**	**0.90**
FCOS	Instance segmentation	N/A	0.51	0.77
SSD VGG-16	Instance segmentation	N/A	0.27	0.67
RetinaNet	Instance segmentation	N/A	0.49	0.72
DeepLab V3 ResNet-101	Semantic segmentation	**0.51**	**0.49**	**0.89**
DeepLab V3 ResNet-50	Semantic segmentation	0.45	0.40	0.86
DeepLab V3 MobileNet	Semantic segmentation	0.40	0.37	0.72
Lite R-ASPP MobileNet	Semantic segmentation	0.42	0.37	0.73
FCN ResNet-50	Semantic segmentation	0.42	0.43	0.81

Further research

- UNet-based models: UNet++, UNet 3+, etc.
- Combined models: Mask R-CNN, etc.
- Loss functions: Focal loss, Tversky loss, DICE loss and combinations
- Pre-training using other wood segmentation datasets