Segmentation of Knot Defects on Coniferous Lumber Surface Using Deep Neural Network

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Introduction

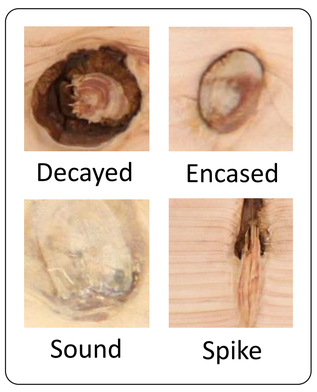
For using wood practically, it is necessary to objectively and speedily detect and assess their defects such as wood knots. Visual lumber grading or defect classification by human eye may result in differences due to subjective decisions. Deep learning technology, which has recently been increasingly used in computer vision for image analysis and pattern recognition due to its high accuracy and speed, was studied to detect and segment surface knots of lumber in this study.

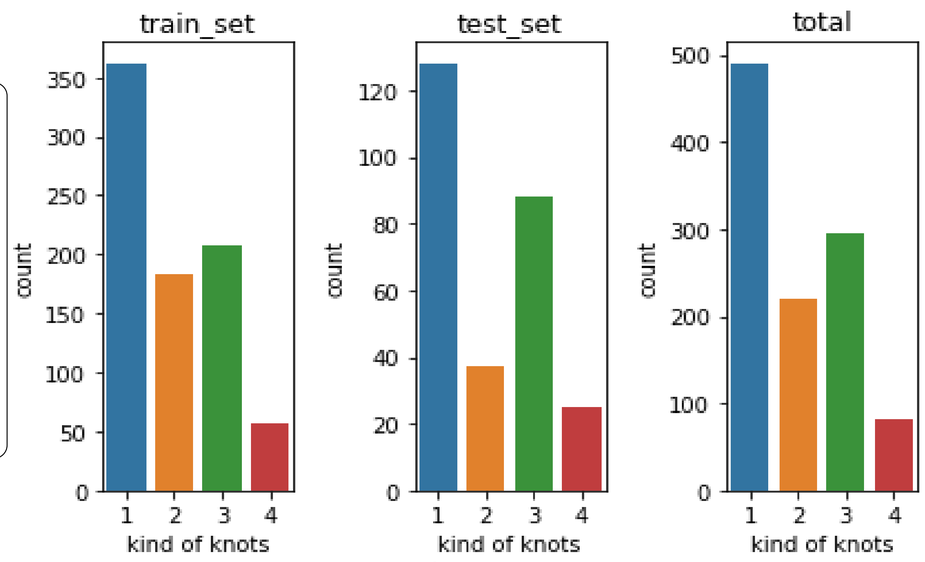
Materials & Methods

938 Wood images were obtained from larch, red pine, Korean pine, cedar, cypress, D- fir, and radiata pine. 1172 Images of four kinds (Decayed, Encased, Sound, Spike) of knot were extracted from the wood images. With dataset on type and location of the knots, learning algorithm was proceeded. The dataset was split into training and test sets for validation with the ratio of 4:1.

Mask R-CNN (Regions with Convolutional Neural Network) model was performed using ResNet101 to learn knot segmentation based on Feature Pyramid Network.

Knot Image Preparation total : 1,172,knots



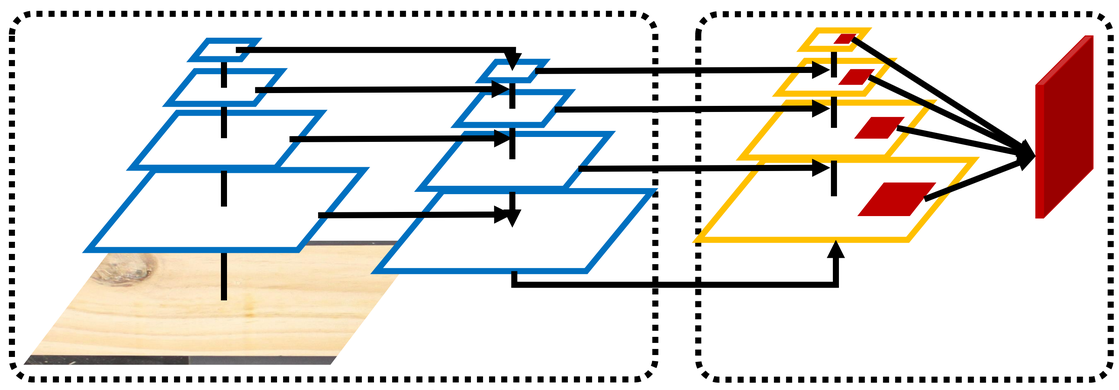


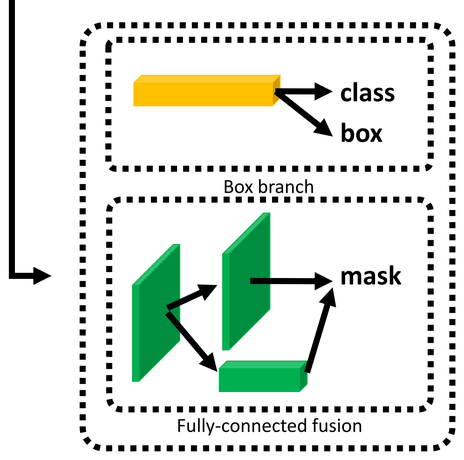
Train : Test = 4 : 1

Model architecture(ResNet101)

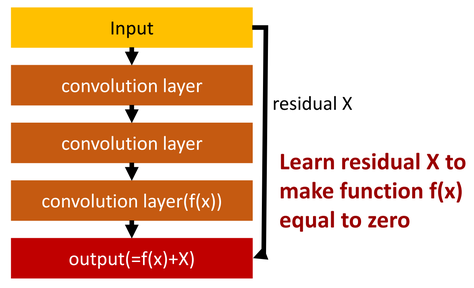
The Feature Pyramid Network is a method for improving resolution to a compressed feature map by adding a low-resolution feature map image and a high-resolution image using interaction of the top-down pathway and bottom-up pathway. The reduction in computation speed due to resolution correction was compensated by applying the residual network.

Feature Pyramid Network, whose strides were 4, 8, 16, 32 and 64, was used as a structure for image pre-processing. Region Proposal Network, whose anchors were 32, 64, 128, 256 and 512, was applied to the technique for detecting and partitioning knots.



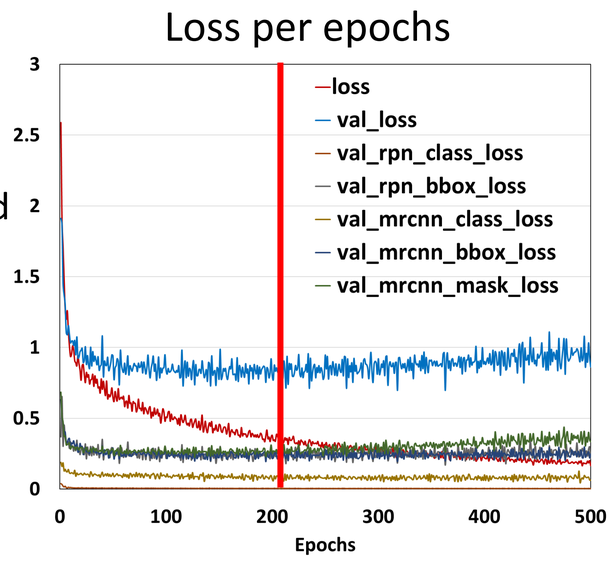


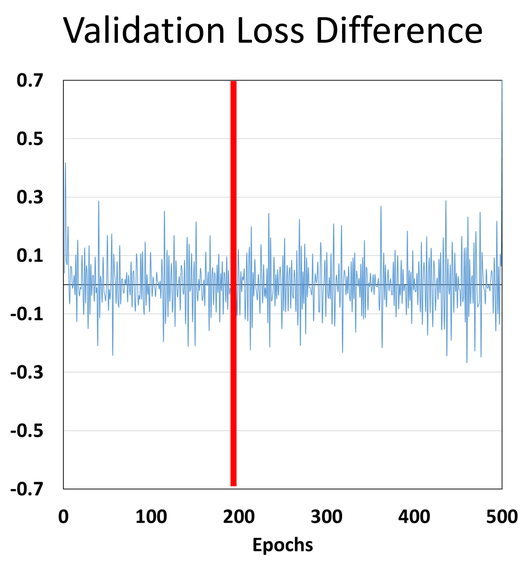
- Image shape : 2048 × 2048 × 3
- FPN strides : 4, 8, 16, 32, 64
- RPN anchors : 32, 64, 128, 256, 512
- Epochs : 500
- Steps per epochs : 100
- Model : resnet101



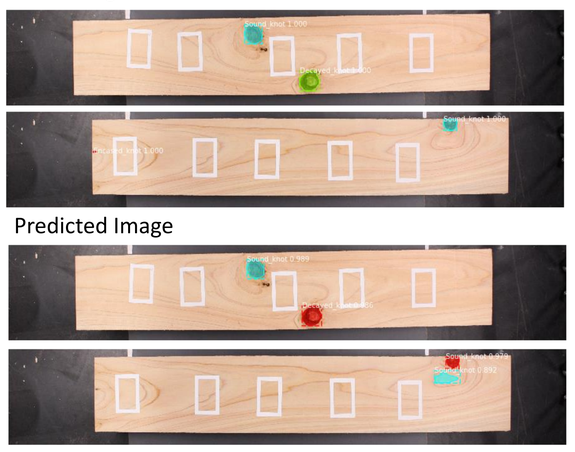
Results & Discussion

Mask R-CNN model used in this study shows high performance in image segmentation of wood surface knots, even some wooden patterns were detected as a knot. Overfitting occurred after 202nd epoch of learning, at that time, minimum loss of the model was 0.35%. Also, even there was a large difference in the number of images by knot types, the model does not show a drastic bias regardless of the difference in the number of images. It is expected that the knots can be segmented with higher accuracy by further massive training of various types.





- End of learning at the point where validation loss rises after 202nd epoch
- End of learning : 202 epoch
- Validation Loss at end of learning : 0.3497
- Train Image



- Predicted Image

Conclusion

As a result of learning the knot of the wood surface, there was a deviation of the image by the type of knot, and the knot of the wood surface could be detected with high accuracy despite the varying size of the knot. As a result of 200 times of learning, the overfitting on the learning image was occurred, and the wooden pattern was detected as knot. However, since it was possible to classify with high accuracy, it is expected that the knots can be segmented with higher accuracy by further learning various knot types.