Selected Topics of Deep Learning Application in Forest Research

Fanyou Wu

Supervised by

Dr. Rado Gazo (Co-Chair), Dr. Eva Eaviarova (Co-Chair),
Dr. Bedrich Benes and Dr. Henry J. Quesada

Table of Contents

Chapter.0

Preface

0 About Me – Machine Learning Competition

~ 60k $ Cash

2 Champions

> 85% Top 10

2017
- Dahang Cup, 2nd, 7600 $
- Alibaba Cloud Challenge, 6th, 1500 $

2018
- JDD 2018, 2nd, 23000 $
- Alibaba Cloud Challenge, 8th, 1500 $

2019
- **IJCAI-19 AIBS, 1st, 5000 $**
- KDD CUP 2019, 4th, 1000 $

2020
- **KDD CUP 2020 RL track, 1st, 8000 $**
- NeurIPS 2020 Traffic4cast, 2nd, 5000 $

2021
- CVPR 2021 AgricultureVision, 2nd, 4200 $
- KDD CUP 2021 RL track, 10th, 500 $

0 About Me – Machine Learning Application Research

4 Journal Paper

4 Proceeding

13 citations

Forestry

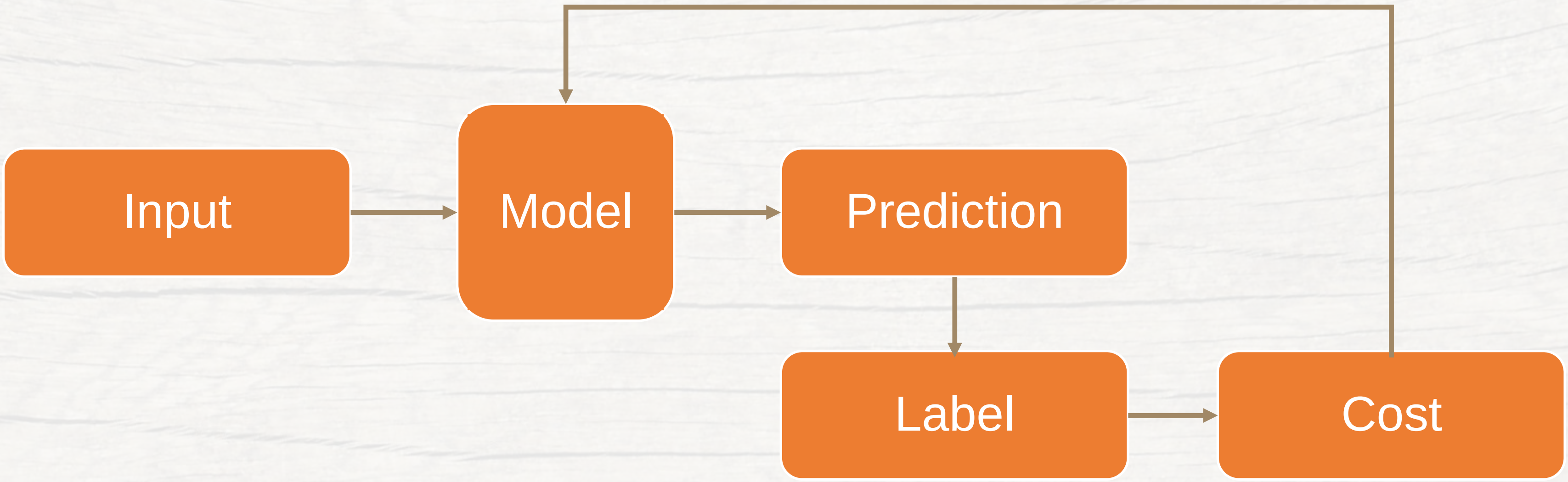
Transportation

Machine Learning

- **Supervised Learning**
- Unsupervised Learning
- Reinforcement Learning

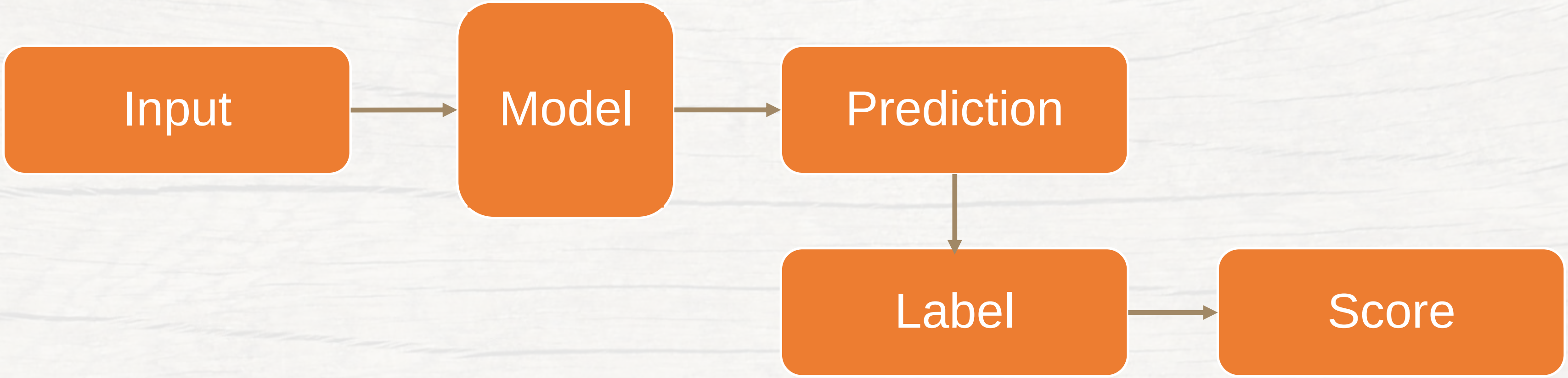
Here we focus on Supervised Learning

- **Training**
- Evaluation
- Testing



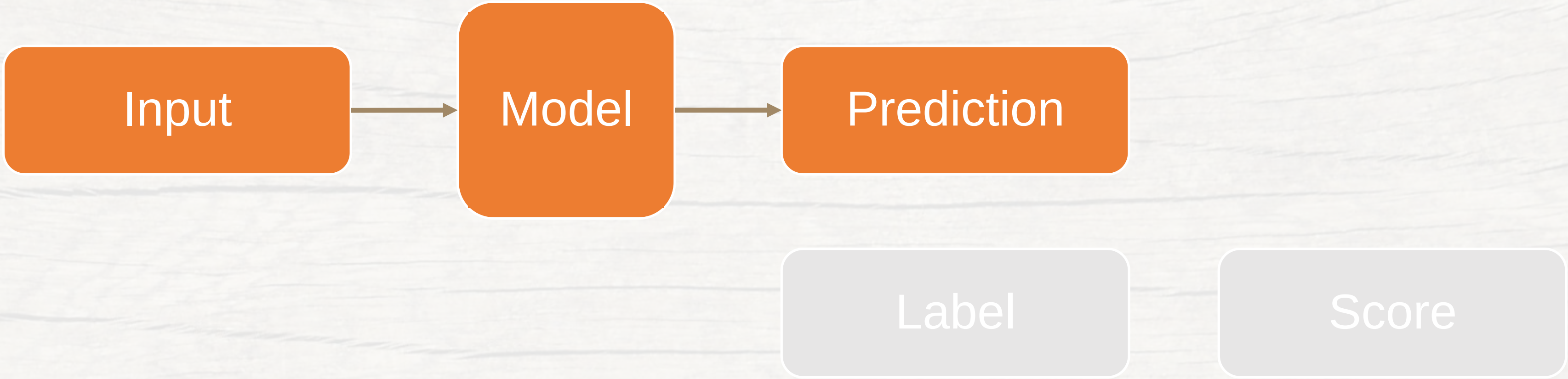
Here we focus on Supervised Learning

- Training
- **Evaluation**
- Testing

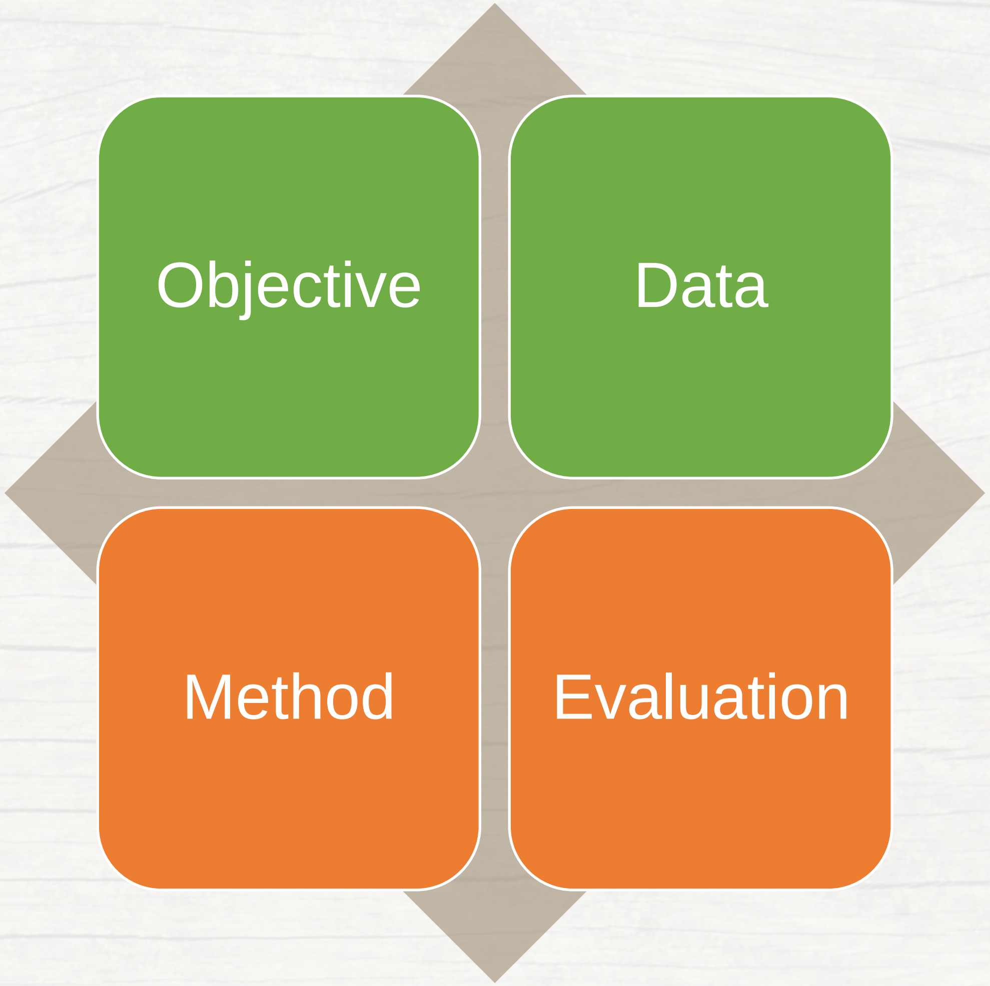


Here we focus on Supervised Learning

- Training
- Evaluation
- **Testing**



- Most people in Computer Science focus on method and evaluation.
- While in Forestry, people more cares about objectives and data.



0

Machine Learning in Forestry

- **Machine Learning Research in Forestry is poplar now.**
- Machine Learning Research in Forestry varies.

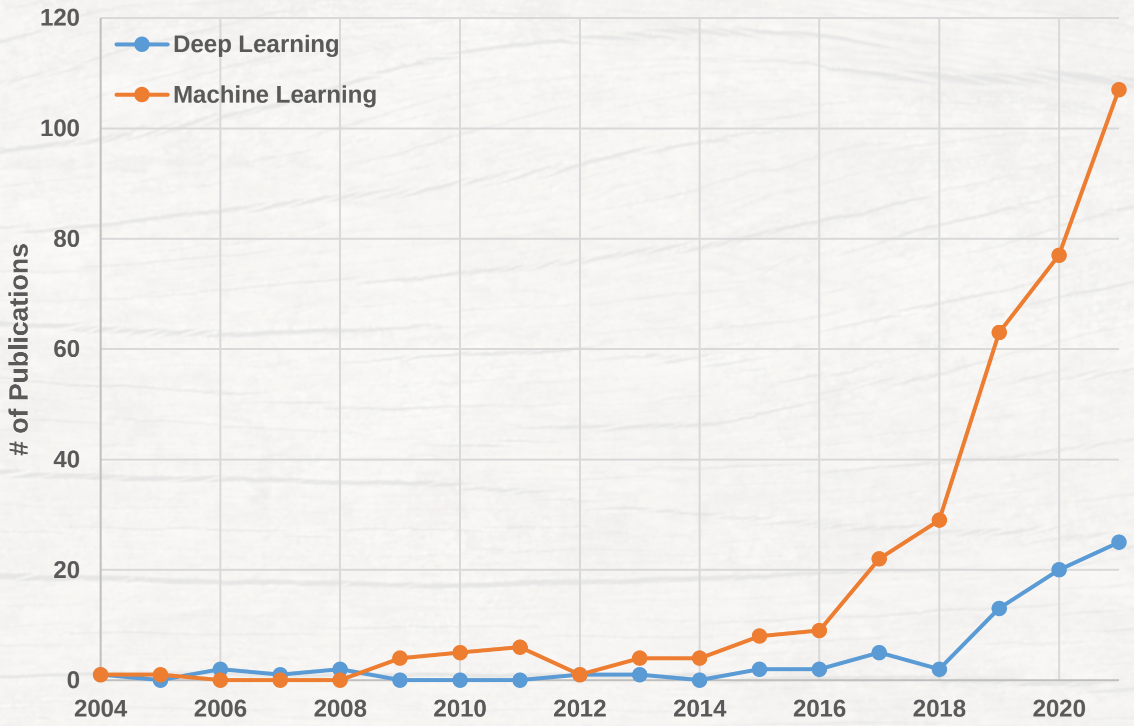


Figure X. The trends of Machine Learning Research in Forestry. Data source: Web of Science.

0 Machine Learning in Forestry

- Machine Learning Research in Forestry is poplar now.
- **Machine Learning Research in Forestry varies.**

- Different Data type
  - Soundscape
  - **2D Images**
  - 3D cloud point
  - Other Remote Sensing data
- Different Objectives
  - Biodiversity
  - Forest Profiling
  - Wildlife
  - **Forest Products**

0 Objective

In this report, we investigated the potential to apply deep learning to ~~forestry-related tasks~~.

wood and bark

Chapter.1

Wood Identification

Wu, F., Gazo, R., Haviarova, E., & Benes, B. (2021). Wood identification based on longitudinal section images by using deep learning. *Wood Science and Technology*, 55(2), 553-563.

1 Introduction

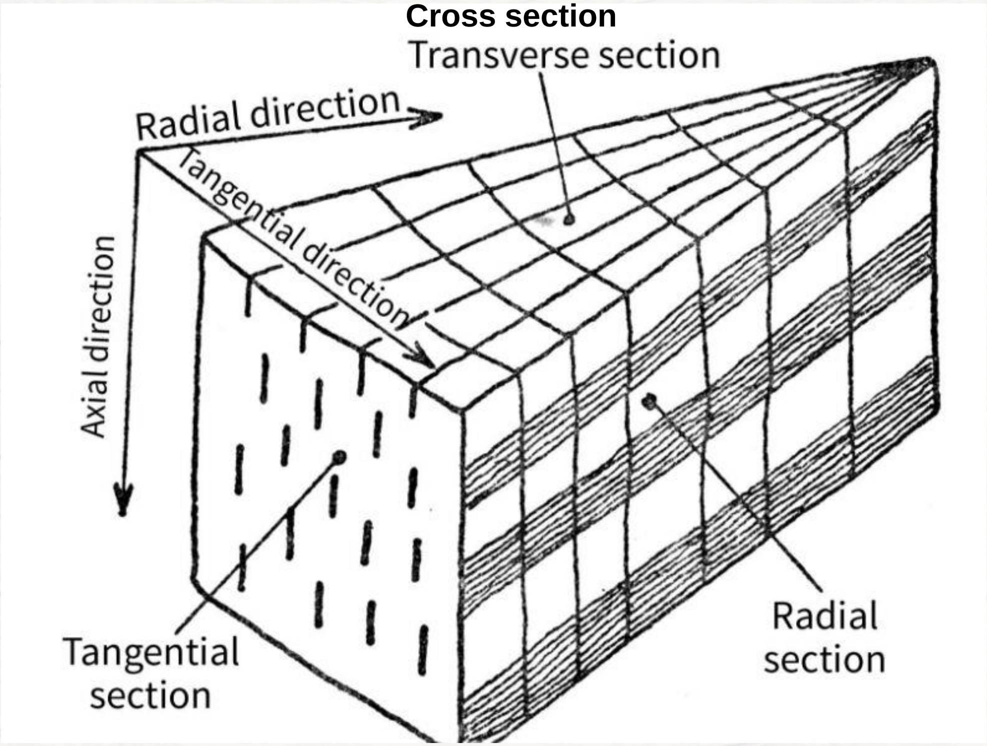


Figure 1.1. Three Wood Sections*.

- Difficulty to identify speices
  - Cross << Radial <= Tangential
- Commonness in industry
  - Cross >> Radial >= Tangential

Longitudinal

One contradiction in lumber identification

* https://marette.smk.dk/-9711.html

1 Material

- 11 Hardwood Speices
- 3158 # board
- Private Dataset
- Relative low quality
- Longitudinal Section

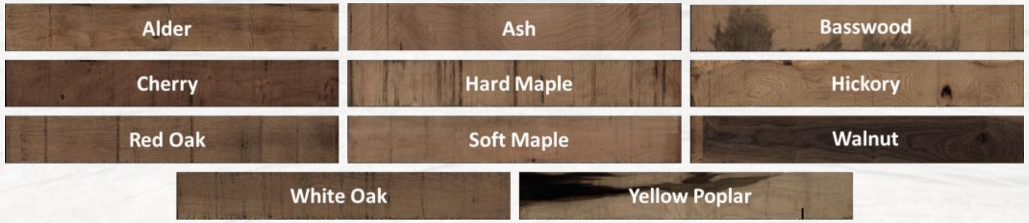


Figure 1.2. Sample images. The area of one pixel corresponds to 0.004 mm^2.

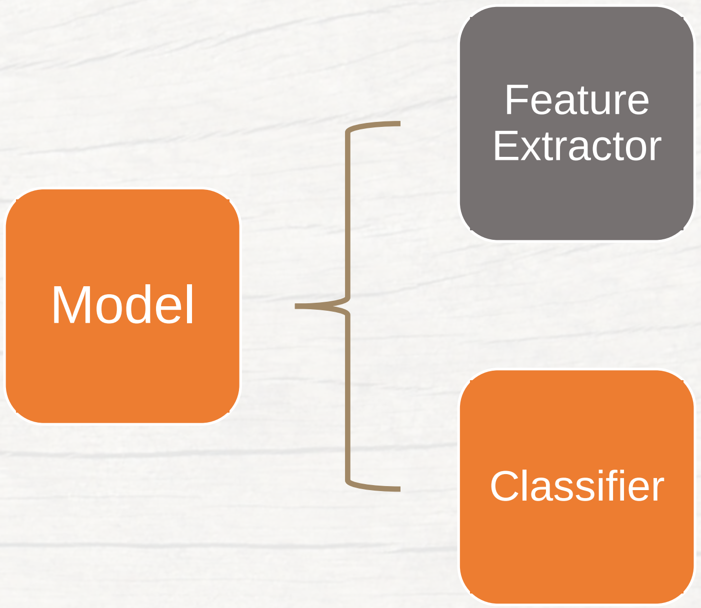
Speices	Common Name	Board #	Patch #
Alnus serrulata	Alder	81	15714
Fraxinus sp.	Ash	200	2478
Tilia americana	Basswood	40	480
Prunus serotina	Cherry	48	576
Acer saccharum	Hard maple	818	9816
Carya ovata	Hickory	13	156
Quercus rubra	Red oak	478	5736
Acer saccharinum	Soft maple	720	8640
Juglans nigra	Walnut	66	792
Quercus sp.	White oak	586	7032
Liriodendron tulipifera	Yellow poplar	108	1296
Total		3158	52716

Table 1.1. Species list: Board # represents the number of boards we screened, and patch # is the final patch (70×70 pixels) count for each species. Alder has the original resolution of 500×1000 pixels which is 20 times larger than other boards.

1 Method – Texture Classification

- **Feature extraction + Simple Classifier**
  - Gray-Level Co-Occurrence Matrix (GLCM)
  - Local Binary Pattern (LBP)
  - Gabor filters

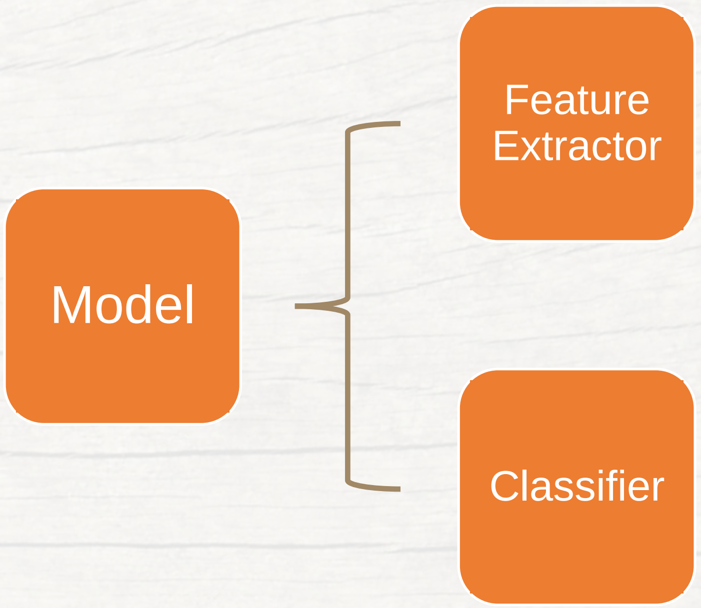
- End-to-end Method
  - Deep Learning



Method – Texture Classification

- Feature extraction + Simple Classifier
  - Gray-Level Co-Occurrence Matrix (GLCM)
  - Local Binary Pattern (LBP)
  - Gabor filters

- **End-to-end Methods**
  - **Deep Learning**



1 Method – Convolution Neural Network (CNN)

Recent CNNs are comprised of groups of **convolutional**, **pooling**, **activation**, and **fully-connected linear** functions and they include hundreds of thousands connections.

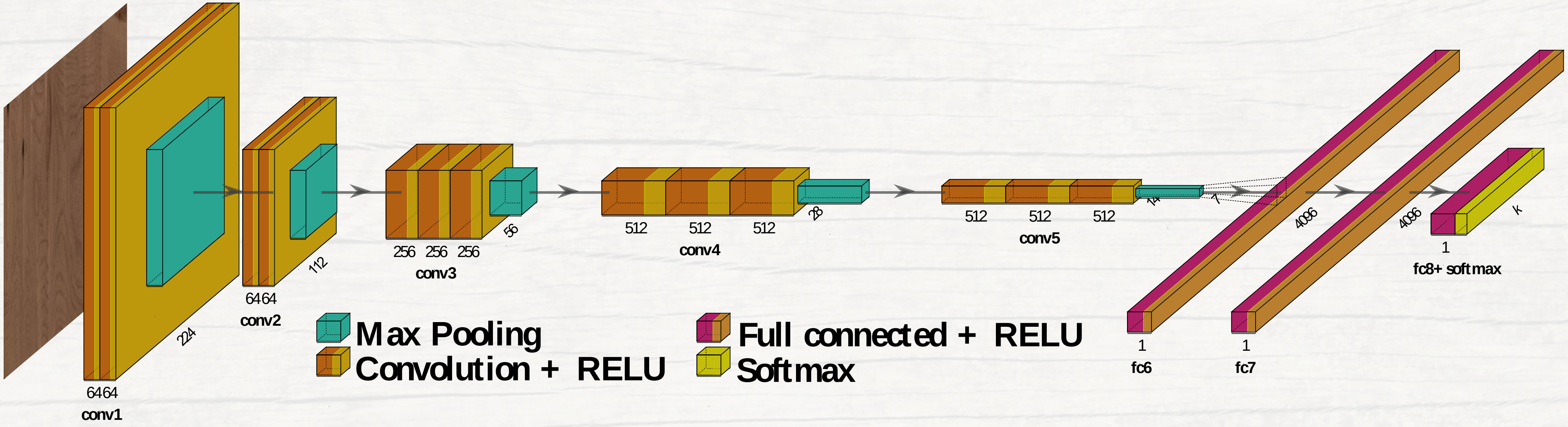


Figure 1.3. A schematic diagram of VGG-16 Architecture. Each cuboid represents the output shape after certain operations

1

Method – Cross Validation

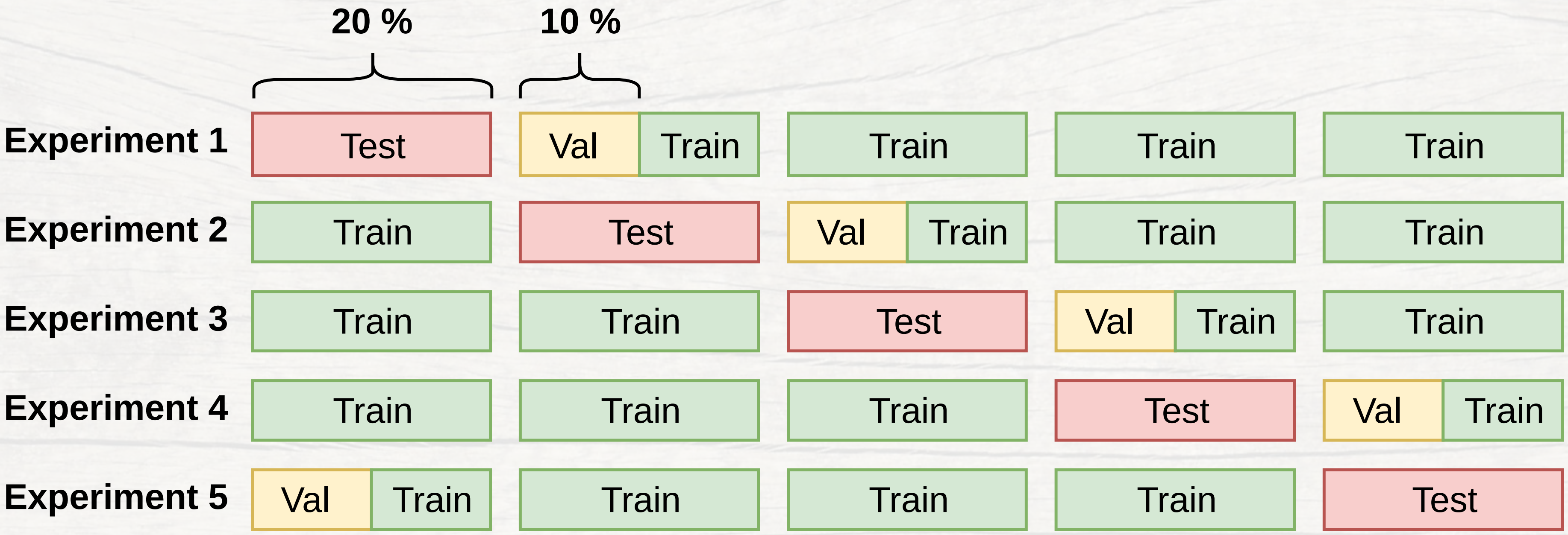


Figure 1.4. Visualization of the cross-validation and splitting of data. Test, Val, and Train represent test set, validation set, and train set, respectively. A rectangle is 20 % of the whole data.

1 Result and Discussion

- The performance order of the three model architectures is within prediction.
- Ensemble models Works.

Data Level	Model	Accuracy	Macro F1
Patch	ResNet-50	0.9519±0.0065	0.8893±0.0231
	DenseNet-121	0.9384±0.0078	0.8634±0.0323
	MobileNet-V2	0.9352±0.0185	0.8507±0.0363
	Average ensemble	**0.9560±0.0075**	**0.8944±0.0330**
Board	ResNet-50	**0.9815±0.0079**	**0.9558±0.0237**
	DenseNet-121	0.9755±0.0088	0.9408±0.0401
	MobileNet-V2	0.9712±0.0095	0.9076±0.0446
	Average ensemble	0.9772±0.0087	0.9424±0.0420

Table 1.2. Model performance. The value is represented as mean ± variance for 5 models

1 Result and Discussion

Predicted Label

True Label

		1	2	3	4	5	6	7	8	9	10	11
Alder	1	1	0	0	0	0	0	0	0	0	0	0
Ash	2	.006	.900	.003	0	.027	.009	.016	.010	0	.029	0
Basswood	3	0	.007	.882	.004	.041	0	.011	.036	0	.007	.012
Cherry	4	0	.001	.018	.926	.024	0	.031	0	0	0	0
Hard Maple	5	0	.004	.002	.002	.953	.001	.010	.019	.002	.006	.001
Hickory	6	0	.170	.016	0	.093	.578	.033	0	0	.110	0
Red Oak	7	0	.005	.001	.001	.019	.001	.923	.011	0	.039	0
Soft Maple	8	0	.002	.001	0	.022	0	.005	.963	0	.005	.002
Walnut	9	0	0	0	.001	.342	0	.010	.009	.615	.023	0
White Oak	10	0	.008	.001	0	.008	.001	.034	.006	0	.942	0
Yellow Poplar	11	0	.001	.001	.001	.001	0	.026	.034	0	.003	.933

ResNet-50

		1	2	3	4	5	6	7	8	9	10	11
Alder	1	1	0	0	0	0	0	0	0	0	0	0
Ash	2	0	.872	.003	.001	.029	.028	.008	.012	0	.037	.002
Basswood	3	0	.011	.817	.002	.068	.002	.039	.041	0	0	0
Cherry	4	0	.009	.010	.934	.024	0	.022	.001	0	0	0
Hard Maple	5	0	.005	.003	.003	.938	.002	.018	.018	.003	.009	.001
Hickory	6	0	.236	0	0	.077	.495	.055	.005	0	.132	0
Red Oak	7	0	.006	.001	.001	.021	.001	.906	.011	0	.053	0
Soft Maple	8	.009	.003	.001	0	.025	.001	.010	.935	.001	.011	.004
Walnut	9	0	0	0	.001	.339	0	.012	.012	.612	.024	0
White Oak	10	0	.006	.001	0	.009	.001	.047	.005	0	.931	0
Yellow Poplar	11	0	.001	.001	0	0	.001	.027	.040	0	.004	.926

DenseNet-121

		1	2	3	4	5	6	7	8	9	10	11
Alder	1	1	0	0	0	0	0	0	0	0	0	0
Ash	2	0	.888	.004	.001	.029	.013	.020	.004	0	.040	.001
Basswood	3	.011	.002	.891	.004	.046	0	.005	.025	0	.012	.004
Cherry	4	.003	.003	.009	.914	.045	0	.024	.001	0	.001	0
Hard Maple	5	.003	.005	.002	.002	.944	.001	.012	.023	.001	.007	0
Hickory	6	0	.258	.005	0	.187	.331	.038	.016	0	.165	0
Red Oak	7	.001	.006	0	.002	.023	0	.906	.012	.001	.048	.001
Soft Maple	8	.001	.003	.004	0	.029	0	.012	.934	0	.010	.007
Walnut	9	.001	.001	0	0	.342	0	.013	.017	.591	.032	.003
White Oak	10	0	.012	.001	.001	.010	.001	.061	.011	.001	.901	.001
Yellow Poplar	11	0	.002	.007	0	.001	0	.026	.042	0	.007	.915

MobileNet-V2

> 0.9
> 0.1 and ≤ 0.9
≤ 0.1

Figure 1.5. Patch level confusion matrix for three models. The x-axis represents the predicted label of models, and the y-axis represents the true label of the patch. Numbers and their corresponding species names are listed on the y-axis. The numbers represent the proportions of the predicted label for one species and should sum up to one.

Hickory – Dataset size; Walnut vs Hard maple – Dark Stains

1 Result and Discussion

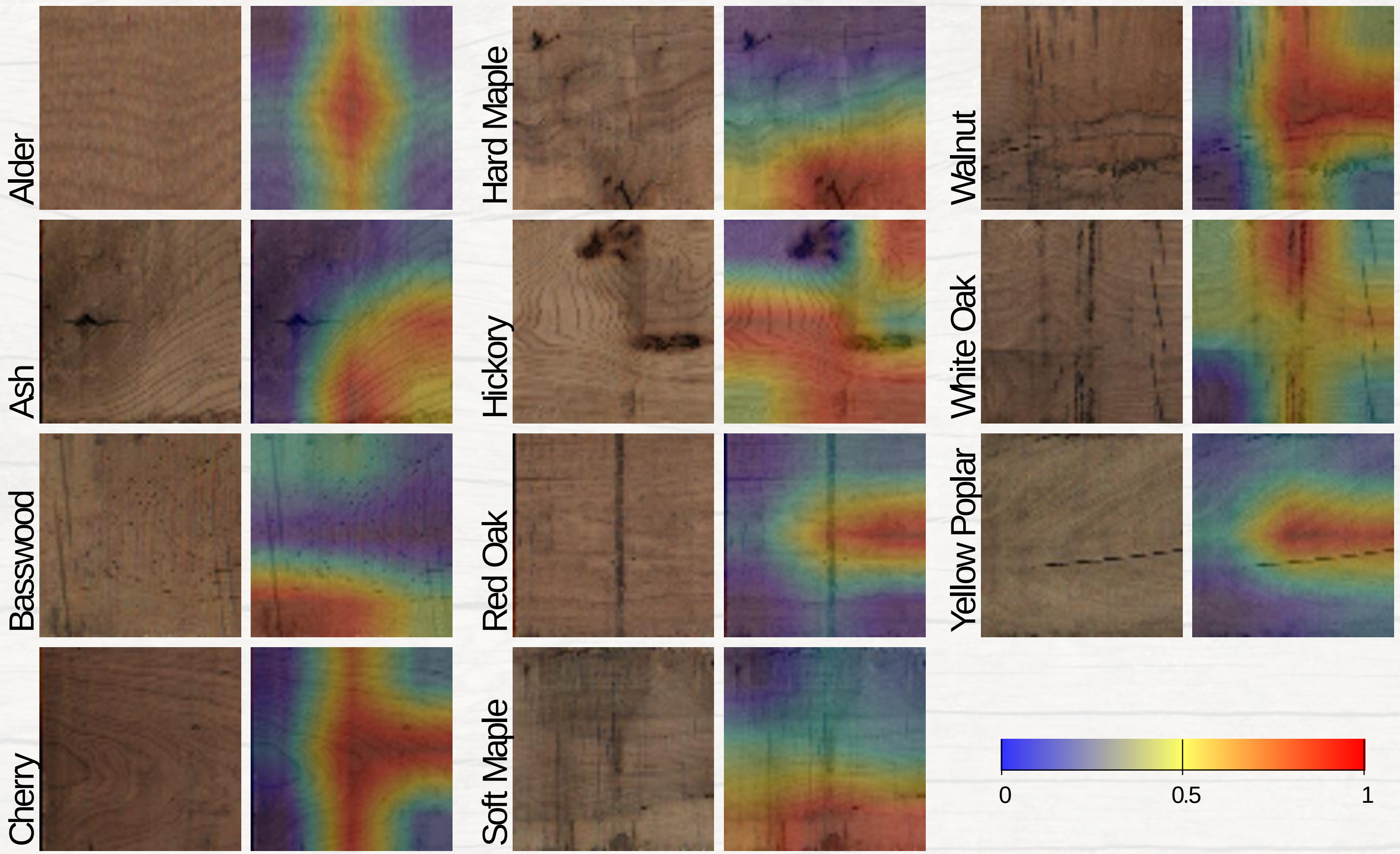


Figure 1.6. Selected Grad-CAM images from ResNet-50. For each species, the left image is the original patch while right image its corresponding Grad-CAM heat map with the background.

Chapter.2

Bark Identification

Wu, F., Gazo, R., Benes, B., & Haviarova, E. (2021). Deep BarkID: a portable tree bark identification system by knowledge distillation. *European Journal of Forest Research*.

Introduction

- Species identification is one of the key steps in the management and conservation planning of many forest ecosystems.
- Existing bark identification systems rely heavily on massive computing power access, which may be scarce in many locations.
- Our approach is deployed as a smartphone application that does not require any connection to a database. Its intended use is in a forest, where internet connection is often unavailable

The needs for an offline bark identification system (App)

2 Material

- A new small dataset called Indiana Bark Dataset (IDB)
- 10 Hardwood Species
- 309 Images from 50 trees

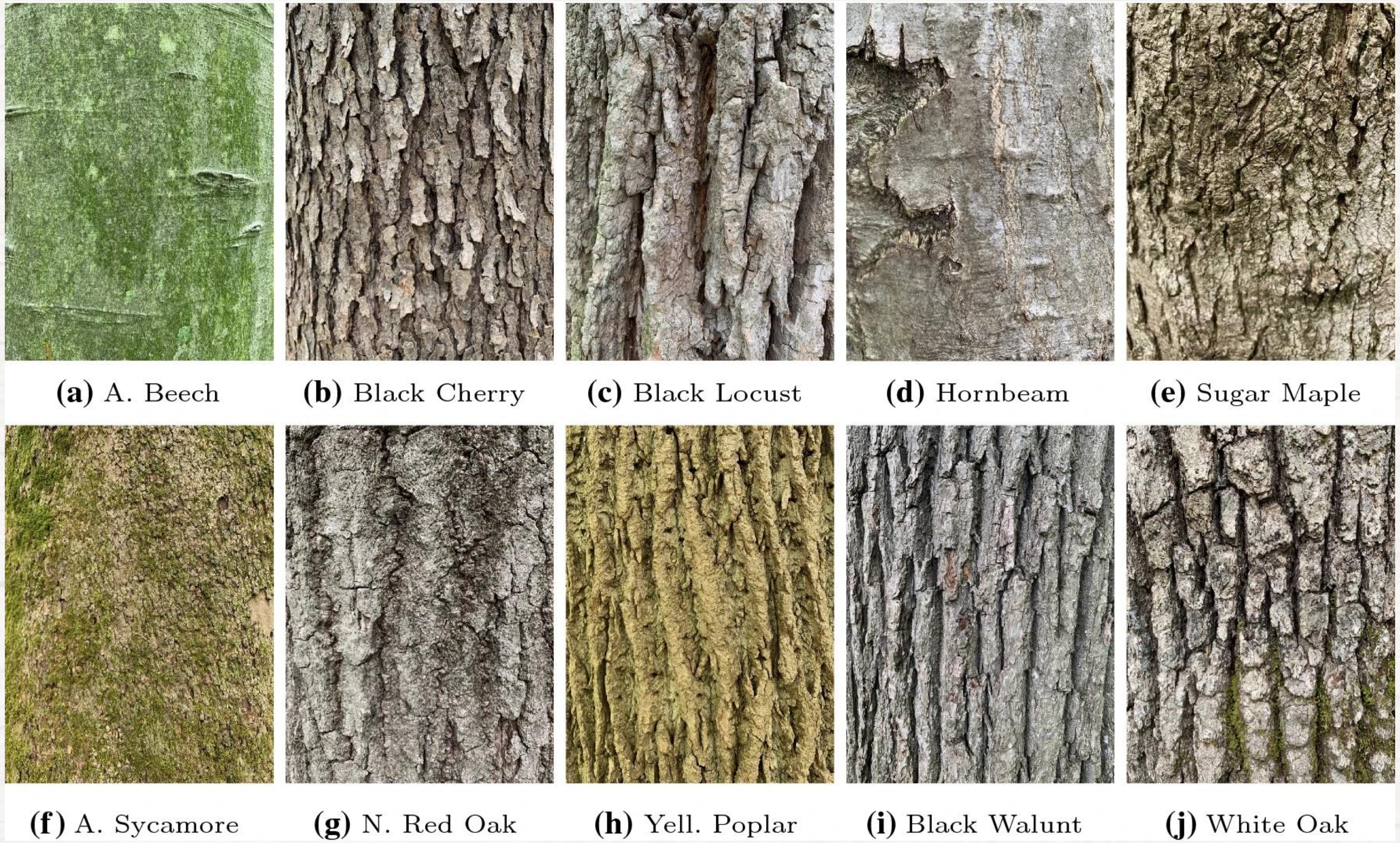


Figure 2.1. Sample images for Indiana Bark Dataset.

2 Material

Dataset	Species	Common name	Trees	Img	SubImgs
Indiana	*Acer saccharum*	Sugar Maple	6	31	1,860
Bark	*Carpinus caroliniana*	American hornbeam	6	30	1,800
	Fagus grandifolia	American Beech	5	24	1,440
	Liriodendron tulipifera	Yellow Poplar	7	35	2,100
	Juglans nigra	Black Walnut	6	30	1,800
	Platanus occidentalis	American Sycamore	6	30	1,800
	Prunus serotina	Black Cherry	6	30	1,800
	Quercus alba	White Oak	6	32	1,920
	Quercus rubra	Northern Red Oak	7	35	2,100
	Robinia pseudoacacia	Black Locust	6	32	1,920
	Total Indiana Bark		61	309	18,540
BarkNet	*Abies balsamea*	Balsam Fir	41	922	28,235
	Acer rubrum	Red Maple	64	1,676	48,925
	Acer saccharum	Sugar Maple	81	1,999	68,040
	Betula alleghaniensis	Yellow Birch	43	1,255	37,325
	Betula papyrifera	White Birch	32	1,285	33,892
	Fagus grandifolia	American Beech	41	840	23,904
	Fraxinus americana	White Ash	61	1,472	53,995
	Larix laricina	Tamarack	77	1,902	114,956
	Ostrya virginiana	American Hophornbeam	29	612	29,723
	Picea abies	Norway Spruce	72	1,324	35,434
	Picea glauca	White Spruce	44	596	19,673
	Picea mariana	Black Spruce	44	885	43,127
	Picea rubens	Red Spruce	27	740	22,819
	Pinus resinosa	Red Pine	29	596	14,694
	Pinus strobus	Eastern White Pine	39	1,023	25,621
	Populus tremuloides	Quaking Aspen	58	1,037	63,247
	Quercus rubra	Northern Red Oak	109	2,724	72,618
	Thuja occidentalis	Northern White Cedar	38	746	19,523
	Tsuga canadensis	Eastern Hemlock	45	986	27,271
	Ulmus americana	American Elm	24	739	27,821
	Total BarkNet		998	23,359	810,843
	Total all		1,059	23,668	829,383

- We also used a publicly available dataset called BarkNet.

- BarkNet used in two ways:
  - Directly train and test in the same dataset
  - Use BarkNet data to pre-train model (1%+)

Table 2.1. Species list for BarkNet and Indiana Bark Dataset. The last column is the number of non-overlapping sub-images given the crop size 224×224 and down sample rate 2. We directly deleted three species from the BarkNet list which are not used in the experiments due to small number of images.

2 Method – Knowledge Distillation

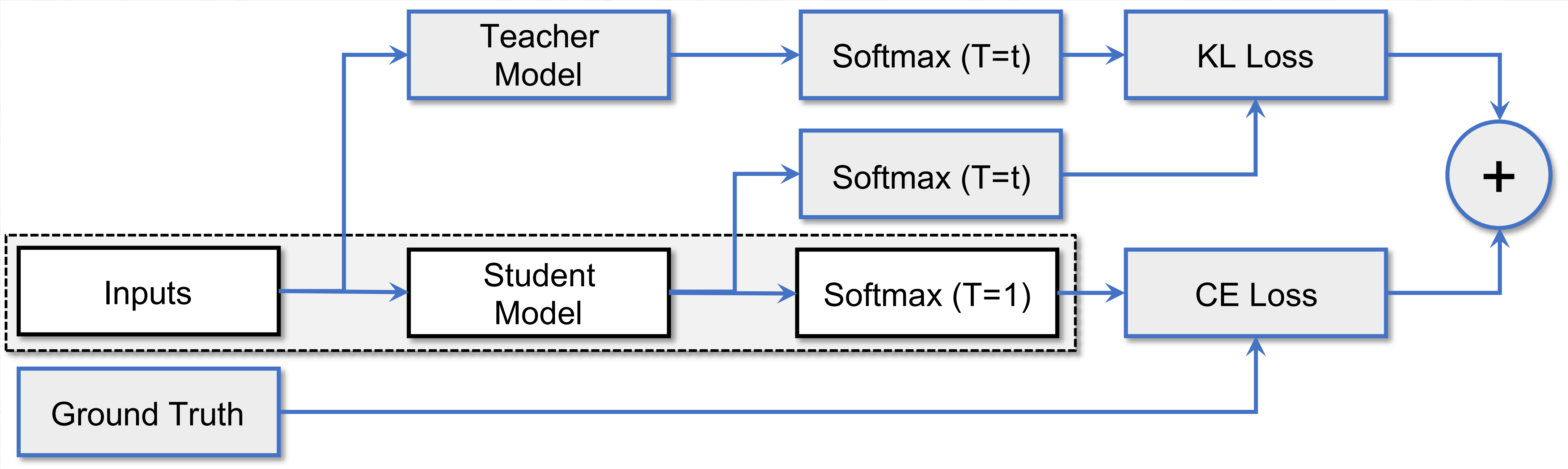


Figure 2.2. Visualization of our implementation of knowledge distillation during training. The black box contains the steps performed during the inference. The KL loss and CE loss are the standard Kullback–Leibler divergence and cross-entropy loss, respectively. t will set to 5 in this study as the parameter of temperature T.

2 Result and Discussion

Dataset	Method	Single Crop	Multiple Crop
IBD	ResNet-34	91.20%	97.09%
	MoblieNet-V2	89.32%	95.80%
	Deep BarkID	91.90%	96.12%
BarkNet	ResNet-34 Carpentier et al. (2018)	87.04%	93.88%
	Boudra et al. (2020)	79.10%	-
	Remeš and Haindl (2019)	90.04%	-
	ResNet-34 (ours)	90.02%	94.62%
	MoblieNet-V2	88.45%	93.51%
	Deep BarkID	88.75%	94.36%

Table 2.2. Model accuracy comparison. '-' indicates the lack of results in the particular article on the given dataset and bold values indicate the best values given each condition. The method column indicates either the model architecture (e.g., MobileNet-V2) or hybrid methods.

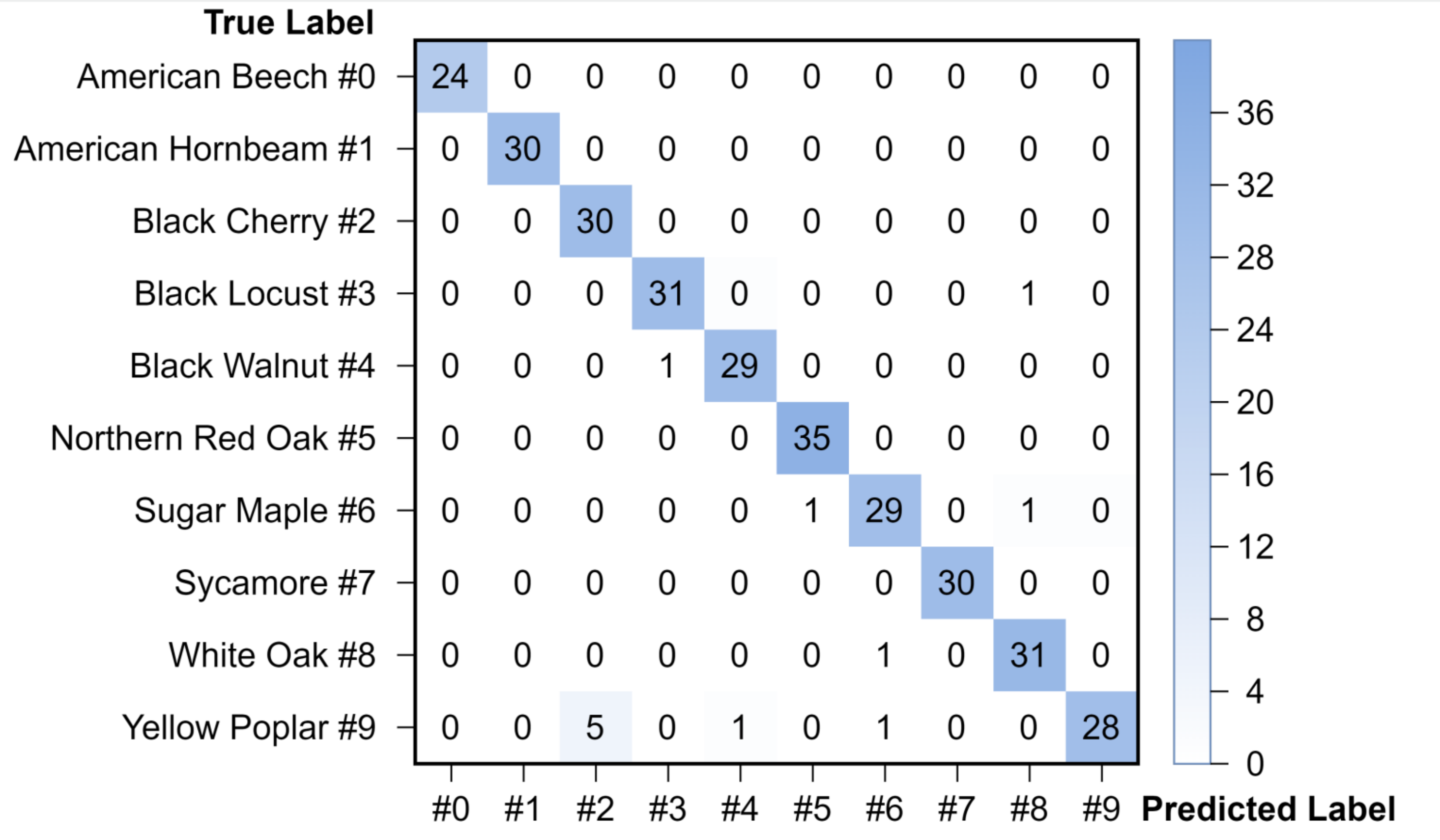


Figure 2.3. The confusion matrix for Multiple Crop of Deep BarkID using Indianan Bark Dataset.

Limitation and Future Research

- Indiana Bark Dataset size is smaller than the BarkNet. It would be useful to capture more images from more trees in different light conditions, different seasons, and different resolutions and retrain our models.

- We have developed an App for a portable iOS device. However, its user interface could be improved. We also plan to deploy it on Android devices.

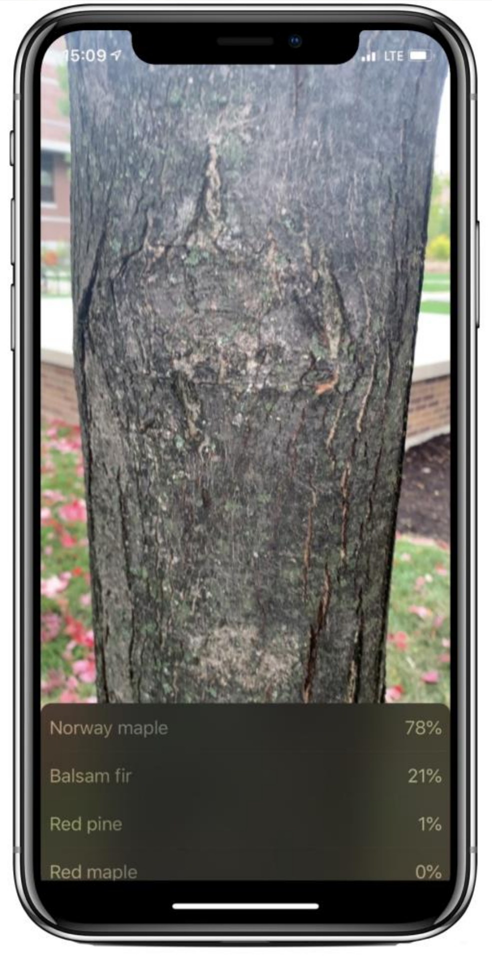


Figure 2.4. A snapshot of Deep BarkID deployed on an iPhone X.

Chapter.3

Growth Ring Detection

Wu, F., Huang Y., Warner, C.C., Benes, B. & Gazo, R. Data Collection and Deep Learning-Based Detection of Wood Growth Ring.

3 Introduction

- Tree-ring dating is not only beneficial for scientific purposes but also is essential in the wood industry.
- Identify growth ring edges is the key step.
- It is difficult to identify from the rough surface even by human raw eyes.
- There is no dataset available publicly.

The needs of growth ring detection of rough wood surface

(a) Rough surface.

(b) Clean surface with some annotations.

Figure 3.1. Sample images of Hickory (Carya spp.).

3 Material

Figure 3.2. We built a special imagining frame with fixed light conditions and calibrated camera.

Species	Common name	Cookies #
Fraxinus spp.	Ash	11
Tilia americana	Basswood	11
Juglans nigra	Black walnut	14
Prunus serotina	Cherry	13
Celtis occidentalis	Hackberry	10
Acer saccharum	Hard maple	14
Carya spp.	Hickory	12
Quercus rubra	Red oak	14
Acer saccharinum	Soft maple	12
Quercus spp.	White oak	14
Liriodendron tulipifera	Yellow poplar	11
Total		136

Table 3.1. Summary of wood samples.

Material – Pipeline

(a) Raw cookie (b) Aligned (c) Cleaned (d) Annotated (e) Back-mapped

Figure 3.3. Overall process pipeline. The raw cookie (a) is enhanced with holes (shown schematically as circles) for alignment (b) and then cleaned (c). Two images (one from each side) are then taken and the images are manually annotated (d). The annotations are mapped back to the raw cookie and used to train our deep neural network model.

Material – Annotation

- Currently, only one slice per cookie is annotated (Width = 128 pixel)
- Each ring edge is represented by 3 points.

Figure 3.4. Annotation Sample of White Oak (*Quercus spp.*).

3 Method – Semantic Segmentation Vs Object detection

- Object Detection (e.g., FASTER-RCNN)
    - Ignores small and close ring objects if parameters are not fine-tuned.
    - Instance Segmentation (e.g., MASK-RCNN)
    - Inherits the features of FASTER-RCNN, but requires larger dataset.

- **Semantic Segmentation**
    - Simple to evaluate but needs heavy post processing to obtain desired plot.
    - Predict heatmap first and then find the local maximum as the ring edge

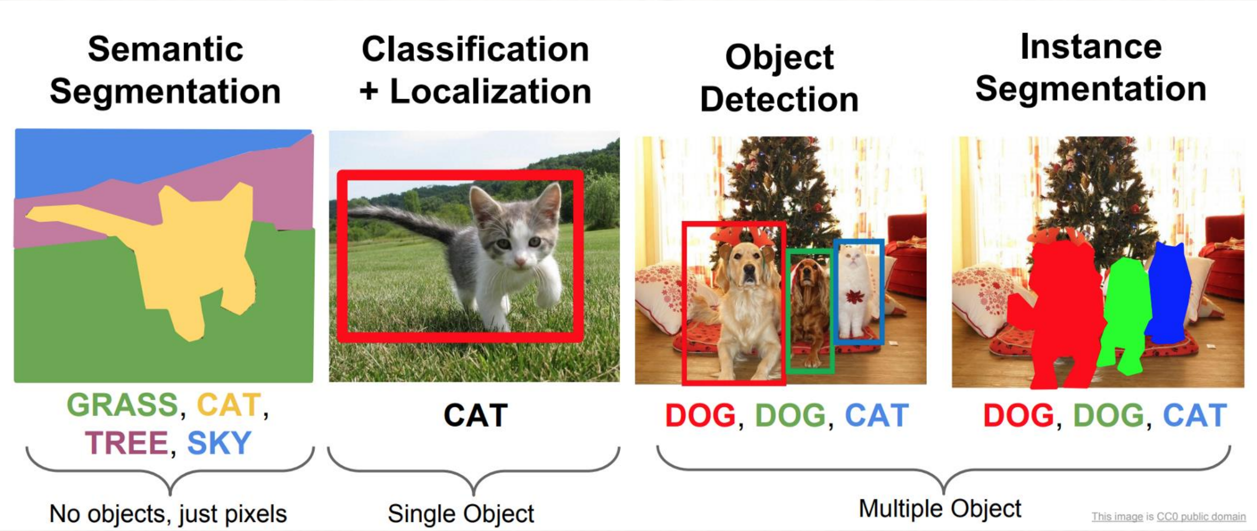


Figure 3.5. Different tasks in computer vision*.

* https://cs231n.github.io/

3

Method – Encoder-Decoder Architecture

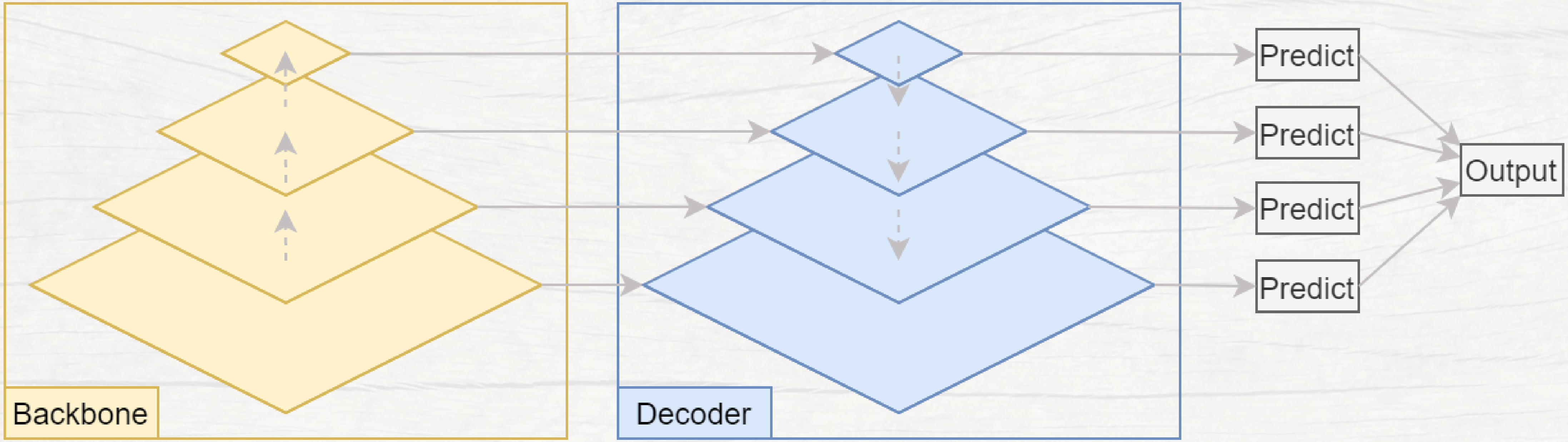


Figure 3.6. Illustration of the FPN architecture.

Encoder-Decoder Architecture is often used in Semantic Segmentation.

3 Result and Discussion

$$REC = \frac{TP}{TP + FN}$$

$$PREC = \frac{TP}{TP + FP}$$

$$F_1 = 2 \times \frac{REC \times PREC}{REC + PREC}$$

Species	Common name	TP	FN	FP	REC	PREC	F1
Fraxinus spp.	Ash	126	6	118	0.95	0.52	0.67
Tilia americana	Basswood	207	32	76	0.87	0.73	0.79
Juglans nigra	Black walnut	251	16	68	0.94	0.79	0.86
Prunus serotina	Cherry	201	26	107	0.89	0.65	0.75
Celtis occidentalis	Hackberry	68	9	18	0.88	0.79	0.83
Acer saccharum	Hard maple	36	6	36	0.86	0.5	0.63
Carya spp.	Hickory	169	18	15	0.9	0.92	0.91
Quercus rubra	Red oak	276	30	126	0.9	0.69	0.78
Acer saccharinum	Soft maple	326	98	89	0.77	0.79	0.78
Quercus spp.	White oak	149	21	145	0.88	0.51	0.64
Liriodendron tulipifera	Yellow poplar	82	11	78	0.88	0.51	0.65

Table 3.2. The performance over different species. The backbone encoder is Efficient-b0, the surface is clean and dry, and the color space is V. We define the correctly detected tree-ring boundaries as true positives (TP), tree-ring boundaries omitted by models as false negatives (FN), and false boundaries introduced by models as false positives (FP).

3 Result and Discussion

Surface	TP	FN	FP	SEN	PREC	F1
Rough	1450	863	1563	0.6	0.48	0.5
Clean Dry	1508	550	1072	0.7	0.58	0.7
Clean Wet	1891	273	876	0.9	0.68	0.8

Table 3.3. The impacts of surface cleanliness. Note that the sum of true positive and false positives is now a constant due to the image alignment and crop reasons.

The current method is not suitable for the rough surface.

3 Future Step

- Annotate more data (3 times more for this paper).
- Use Object detection methods.
- Consider the full area of the wood cookies instead of just one slice.

Chapter.4

Zero Shot Learning for Wood

Wu, F., Liu, Y., Benes, B., Haviarova, E. & Gazo, R. Learn attributes of microscopic wood images based on convolutional neural network.

4 Introduction

In recent decades, many studies have focused on automatic wood identification based on wood image by using Convolutional Neutral Networks (CNN). All of them have good performances, which show the potentials of deep learning in wood identification. However, all of those studies require relatively large replicates for each class, and their scopes are usually narrow down to native species. We believe those studies will raise the committee's attentions to collecting more images of each wood species, but collecting data is always a time-consuming and label-force-intensive job. Therefore, we should seek an alternative way to automatic wood identification, which fits most wood collections' current situation. These collections own thousands of species, each of which contains only a few or even one sample and a complete feature description with multiple-entry key, as in InsideWood.

Material

Name		#
# of Images	**Total**	38,923
	cross section	16,778
	tangential section	13,176
	radial section	8,969
# of Family		254
# of Species		7,426
Magnification		x1 ~ x300
Resolution		1000x1500

Table 4.1. Data Descriptions.

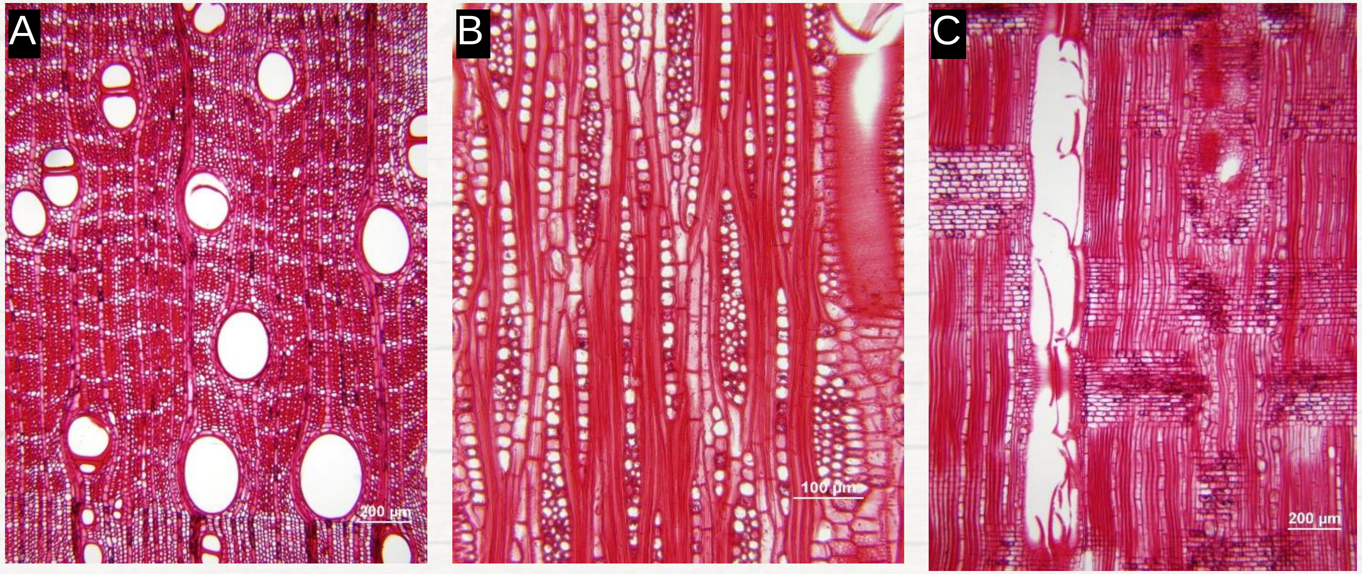


Figure 4.1. A set of sample images of True Hickory (*Carya aquatica*). A, B and C are cross, tangential and radial sections respectively.

4 Method – Zero shot Learning

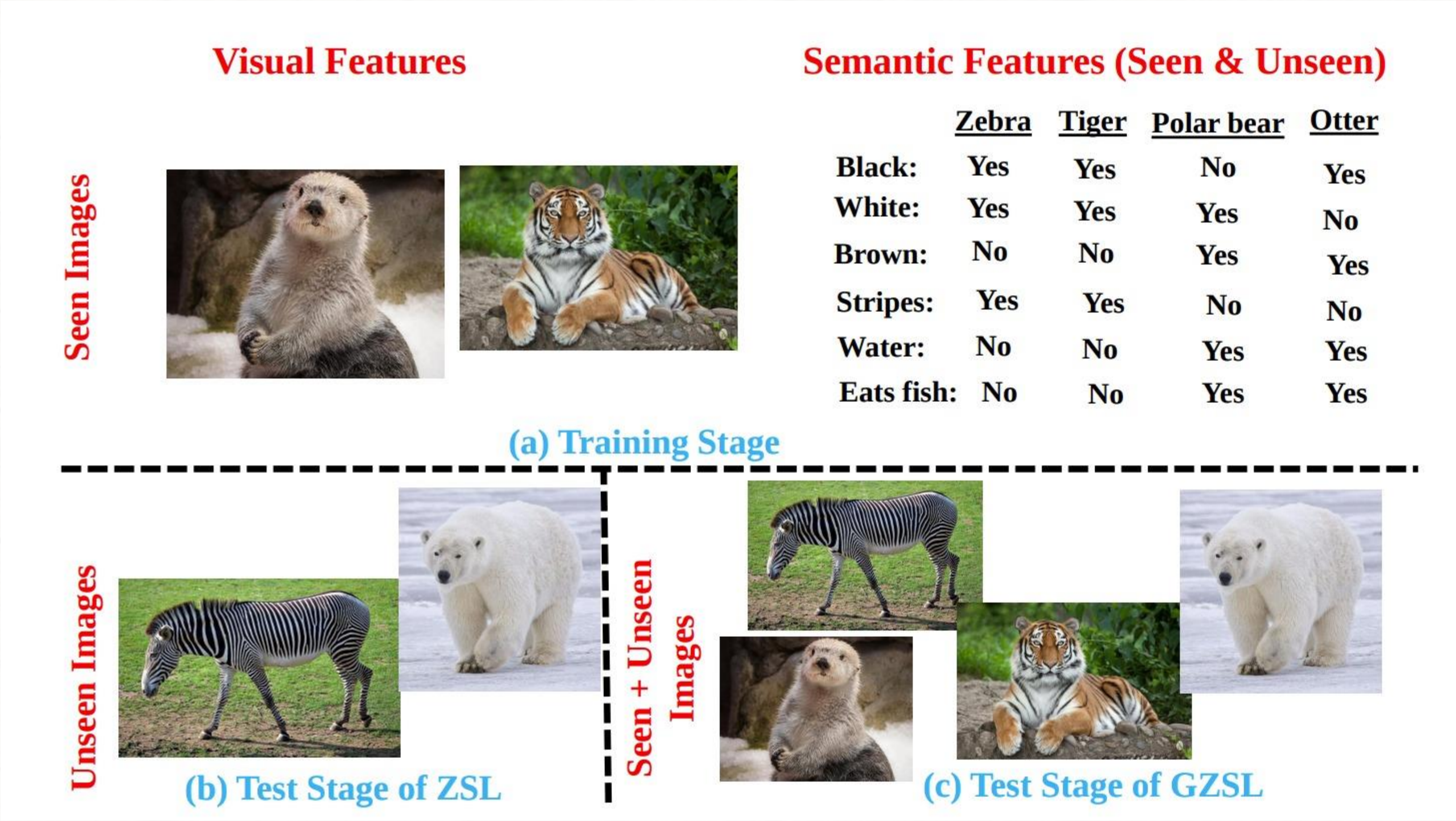


Figure 4.2. A diagram of zero-shot learning*.

* Pourpanah, F. et al. A review of generalized zero-shot learning methods. (2020)

Section	Feature Group	EfficientNet-b1	ResNet-18	MobileNet-V2
Transverse	Growth Rings	0.665	0.675	0.69
	Vessels	0.836	0.833	0.839
	Tracheids and fibres	0.814	0.811	0.814
	Axial parenchyma	0.798	0.792	0.8
	Rays	0.882	0.877	0.883
Longitudinal	Vessels	0.779	0.781	0.786
	Tracheids and fibres	0.732	0.731	0.743
	Rays	0.765	0.764	0.789
	Secretory elements and cambial variants	0.962	0.965	0.962
	Storied structure	0.941	0.941	0.942
	Mineral inclusions	0.931	0.931	0.928

Table 4.2. Attribute accuracy.

4 Future – A Cross Platform App

- A software based on Electron and ONNX
- Aims at identifying most wood speices based on microscopic images

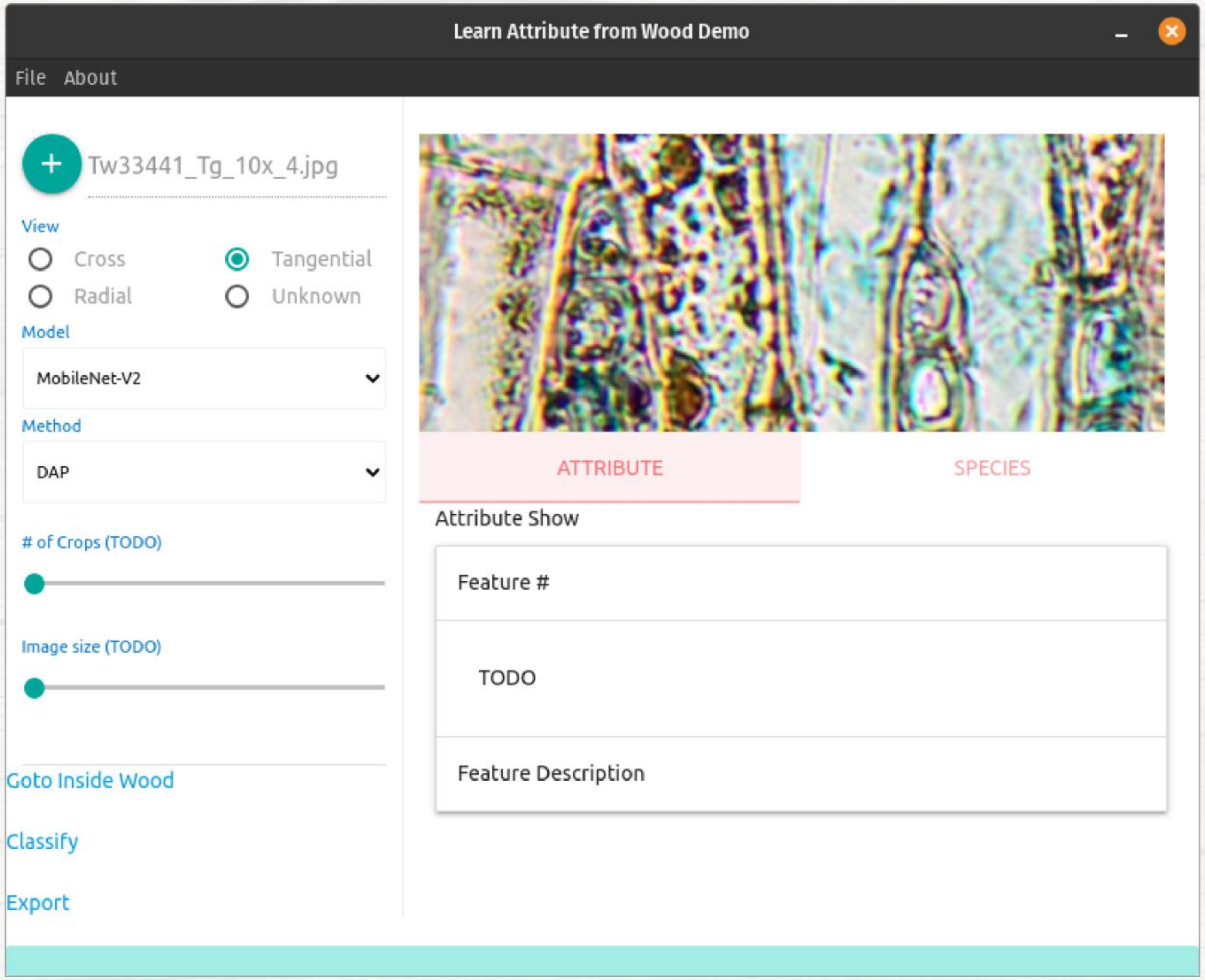


Figure 4.3. An App under development.

Summary

In conclusion, **we applied deep learning to forestry-related tasks and achieved better performance than transitional methods.** Specifically:

- In chapter 1, we investigated the potential use of CNNs for **hardwood lumber identification based on tangential plane images.** We achieved over 95% successful classification rate for a single model and 98% by applying the model ensemble.

- In chapter 2, We developed Deep BarkID, **a light-weight tree species identification application by bark images,** by using deep learning. We achieved 96.12% accuracy for ten tree species classification tasks with the multi-crop setup.

- In chapter 3, we first introduce a new dataset of images of hardwood species annotated for **tree ring detection.** We applied the state-of-the-art semantic segmentation models to the dataset and achieved an overall F1 score of 0.77 for clean images.

- In chapter 4, we combined the observed classes and non-observed classes by distinguishing the attributes of objects and applied **zero-shot learning to microscopic wood images** in InsideWood database.

Acknowledgement

Firstly, I am highly grateful to my supervisors, **Prof. Rado Gazo** and **Prof. Eva Haviarova**, for their valuable advice, continuous support, and patience during my Ph.D. study. Their tremendous knowledge and abundant experience have encouraged me in my academic research.

Also, I would like to thank **Prof. Benes Bedrich** and **Prof. Henry J. Quesada** for their technical support and wise suggestion on my research projects.

I would like to express my gratitude to **my mother, 田国英**, and my **girlfriend 刘倩云**. Without their understanding and support, it would be impossible for me to complete my study.

Finally, thanks to **other friends** in the **Wood Research Lab** and **FNR Department**.