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Wood Species Recognition using Convolutional Neural Network

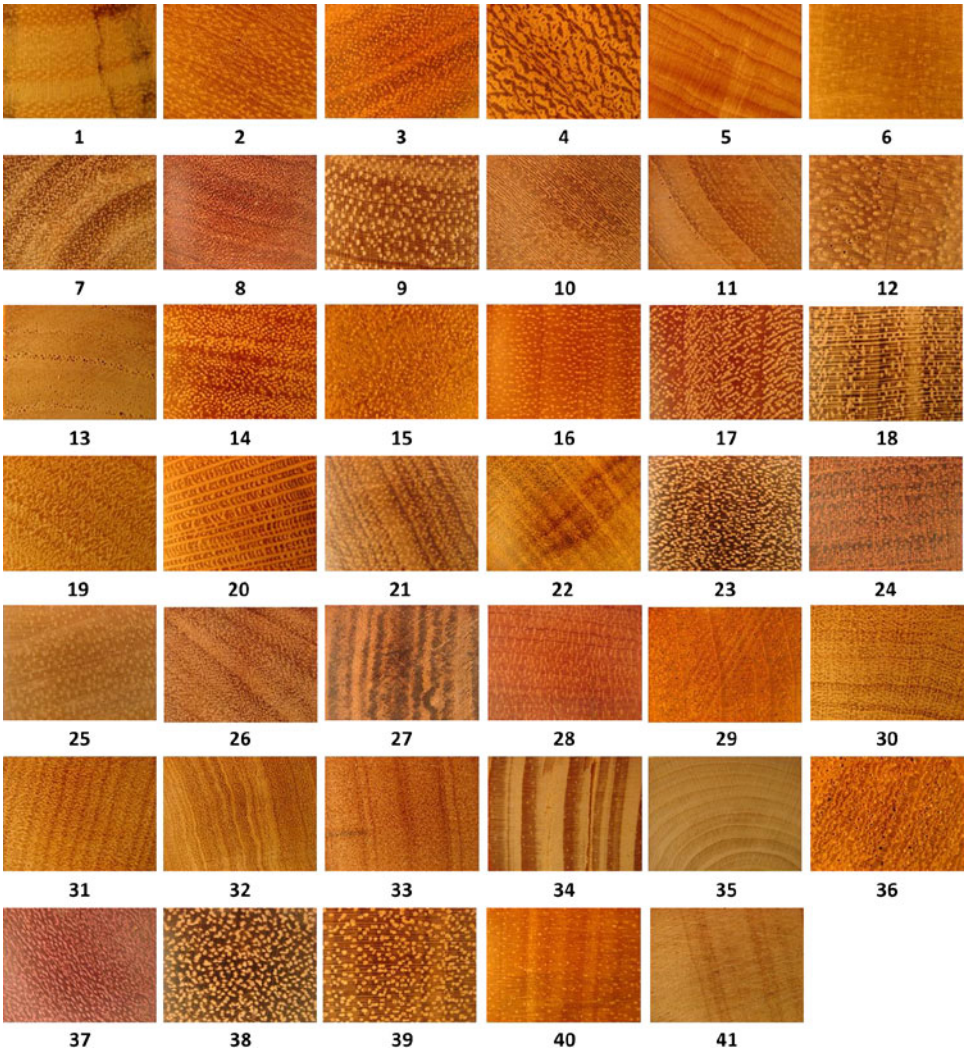


Fig.1 Samples of the database from “Forest species recognition using macroscopic images”, Pedro L. P. Filho etc.

1. Malaysia

“Design of an intelligent wood species recognition system”, M. Khalid, E. L. Y. LEE, R. Yusof, and M. Nadaraj, Centre for Artificial Intelligence and Robotics (CAIRO), University Teknologi Malaysia, 2008.

Data source: Forest Research Institute of Malaysia (FIRM)

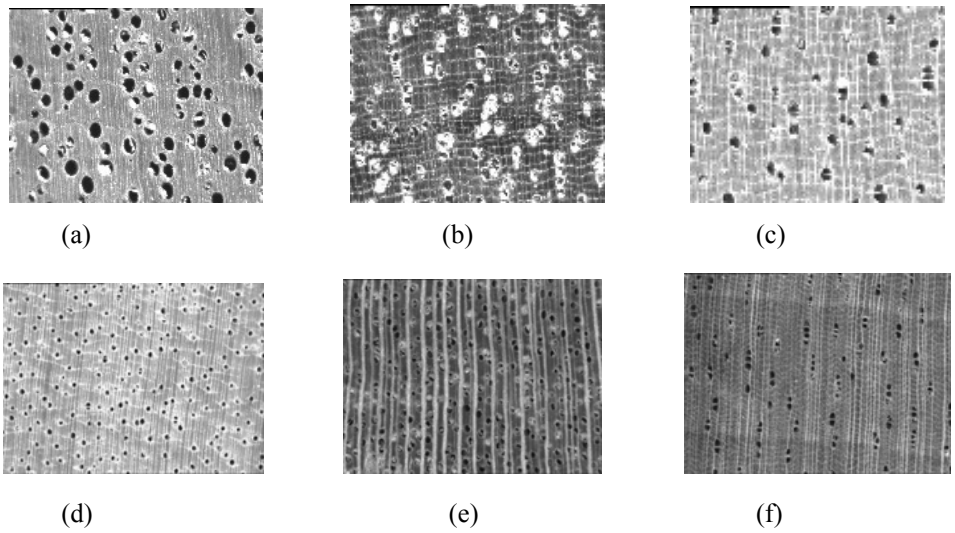


Fig.2 Six e examples of macroscopic anatomy images of Malaysian wood: (a) bintangor, (b) nyatoh , (c) sesendok, (d) ramin, (e) mersawa and (f) jelutong.

Fig.3 A CCD camera with a 40mm extension tube is used to acquire the macroscopic wood anatomy.

20 tropical Malaysian woods, 1,753 images for training, 196 images for testing

multilayer perceptron (MLP) artificial neural network (ANN), ~95%

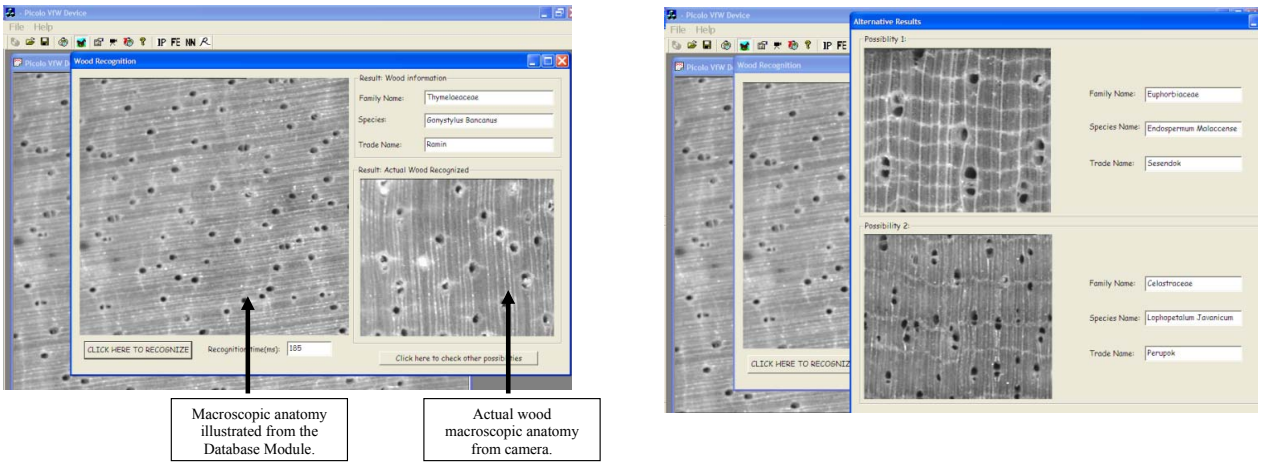


Fig.4 Example of the results given by the Recognition Module of the Wood Recognition System. Visual C++

2. Brazil

“A database for automatic classification of forest species”, J. Martins, L. S. Oliveira, S. Nisgoski, R. Sabourin, Federal University of Parana (UFPR), 2013

112 different forest species belonging to 2 groups (Hardwoods and Softwoods), 85 genera, and 30 families.

catalogued by Laboratory of Wood Anatomy at the Federal University of Parana in Curitiba, Brazil

Total 2,240 microscopic images (20 images per species), resolution 1024x768

Fig. 5 Olympus Cx40 microscope, 100x zoom. The wood sample is cut with a sliding microtome to a thickness about 25μ.

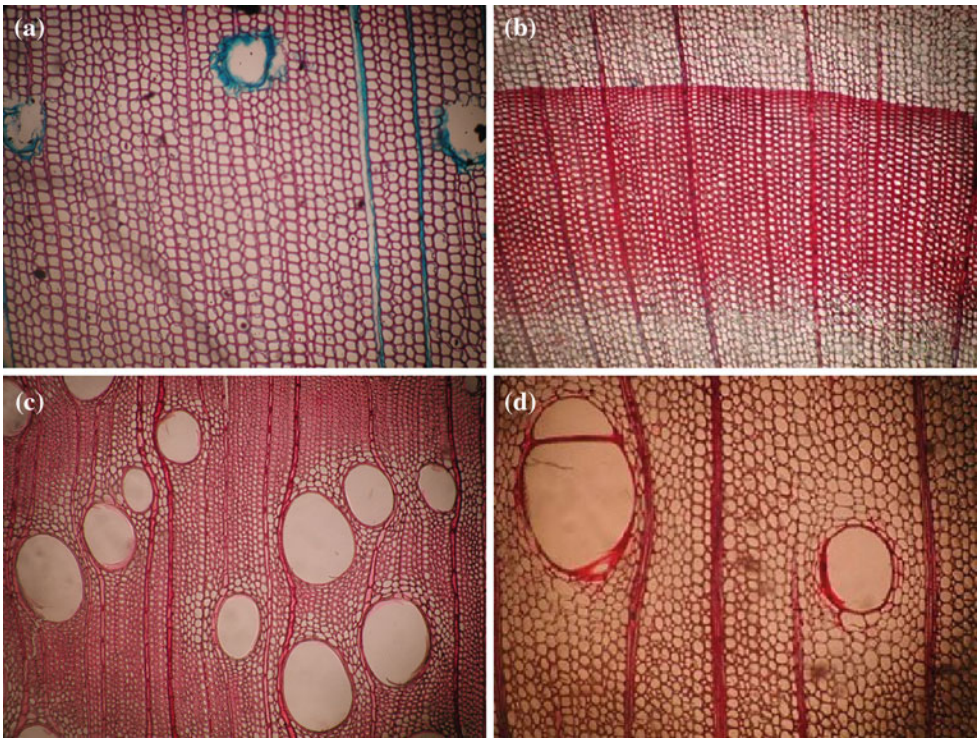


Fig. 5 Species of the database a 21, b 33, c 58, and d 95

1. 2-class problem: 98.6%
2. multi-class problem: 86.0%

Method: Support Vector Machine (SVM) + Local Binary Patterns (LBP)

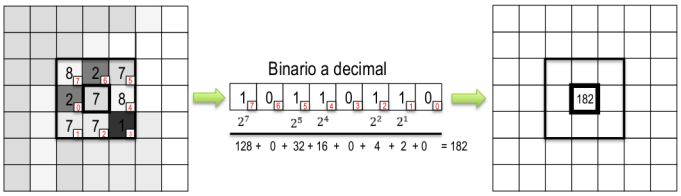


Table 5 Confusion matrices (in %) for the classifiers trained with LBP features

	kNN		LDA		SVM	
	Softwood	Hardwood	Softwood	Hardwood	Softwood	Hardwood
Softwood	79.2	20.8	93.0	7.0	97.2	2.8
Hardwood	1.1	98.8	2.9	97.1	0.7	99.3

Table 6 Summary of all experiments on the testing set

Feature set	Number of features	Rec. rate (%)					
		k-NN	σ	LDA	σ	SVM	σ
Structural	6	92.6	0.8	88.9	0.5	93.1	0.8
GLCM	24	89.0	1.2	95.0	0.1	97.4	0.6
LBP	59	92.3	0.5	95.8	1.1	98.6	0.5

Table 7 Recognition rates for the multi-class problem

Feature set	Number of features	Rec. rate (%)					
		k-NN	σ	LDA	σ	SVM	σ
GLCM	24	46.6	0.6	60.6	1.4	55.3	1.2
LBP	59	70.1	0.5	80.7	0.2	79.3	1.4

“Forest species recognition using macroscopic images”, P. L. P. Filho, L. S. Oliveira, Federal University of Parana (UFPR), 2014

Data source: 41 species of the Brazilian flora, total 2,942 images, were cataloged by the Laboratory of Wood Anatomy at the Federal University of Parana (UFPR).

Table 1 Forest species

ID	Family	Species	Number of images
1	Apocynaceae	*Aspidosperma polyneuron*	43
2	Araucariaceae	*Araucaria angustifolia*	63
3	Bignoniaceae	*Tabebuia* sp.	99
4	Boraginaceae	*Cordia goeldiana*	53
5	Boraginaceae	*Cordia* sp.	51
6	Euphorbiaceae	*Hura crepitans*	41
7	Fabaceae	*Acrocarpus fraxinifolius*	53
8	Fabaceae	*Hymenaea* sp.	82
9	Fabaceae	*Peltogyne* sp.	58
10	Fabaceae	*Hymenolobium petraeum*	99
11	Fabaceae	*Myroxylon balsamum*	75
12	Fabaceae	*Dipteryx* sp.	67
13	Fabaceae	*Machaerium* sp.	87
14	Fabaceae	*Bowdichia* sp.	99
15	Fabaceae	*Mimosa scabrella*	48
16	Fabaceae	*Cedrelinga catenaeformis*	99
17	Goupiaceae	*Goupia glabra*	51
18	Lauraceae	*Ocotea porosa*	99
19	Lauraceae	*Mezilaurus itauba*	64
20	Lauraceae	*Laurus nobilis*	46
21	Lecythidaceae	*Bertholethia excelsa*	72
22	Lecythidaceae	*Cariniana estrellensis*	55
23	Lecythidaceae	*Couratari* sp.	63
24	Meliaceae	*Carapa guianensis*	43
25	Meliaceae	*Cedrela fissilis*	37
26	Meliaceae	*Melia azedarach*	56
27	Meliaceae	*Swietenia macrophylla*	96
28	Moraceae	*Brosimum paraense*	63
29	Moraceae	*Bagassa guianensis*	58
30	Myristicaceae	*Virola surinamensis*	80
31	Myrtaceae	*Eucalyptus* sp.	99
32	Pinaceae	*Pinus* sp.	79
33	Podocarpaceae	*Podocarpus lambertii*	62
34	Proteaceae	*Grevilea robusta*	86
35	Rutaceae	*Balfourodendron riedelianum*	99
36	Rutaceae	*Euxylophora paraensis*	96
37	Sapotaceae	*Micropholis venulosa*	78
38	Sapotaceae	*Pouteria pachycarpa*	94
39	Sapotaceae	*Manilkara huberi*	92
40	Vochysiaceae	*Erisma uncinatum*	98
41	Vochysiaceae	*Vochysia* sp.	59

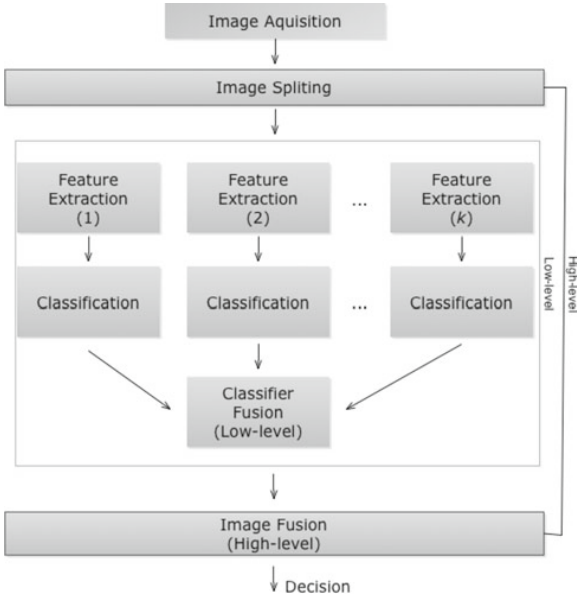


Fig.6 The proposed method

Table 3 Recognition rates achieved by different texture descriptors

ID	Feature	Rec. Rate (%)
1	Color RGB	76.40
2	Color lab	79.50
3	Color mix	56.04
4	GLCM gray	55.97
5	Gabor filters	67.97
6	$LBP_{8,1}$	61.73
7	$LBP_{8,2}$	65.53
8	$LBP_{16,2}$	68.24
9	LBP_{HF}	51.31
10	Fractals	46.46
11	Edges	39.04
12	LPQ	61.77
13	$CLBP\_SMC_{8,1}$	75.05
14	$CLBP\_SMC_{16,3}$	86.24
15	$CLBP\_SMC_{24,5}$	88.60

Table 4 Results of the best combination results

# of Classifiers	Feature sets	Rec. rate (%)
7	$CLBP\_SMC_{16,3}$, $CLBP\_SMC_{24,5}$, Color RGB, Color Lab, Gabor, $LBP_{16,2}$, Fractals	94.27
4	$CLBP\_SMC_{24,5}$, Color Lab, Gabor, $LBP_{16,2}$	94.27
7	$CLBP\_SMC_{16,3}$, $CLBP\_SMC_{24,5}$, Color RGB, Color Lab, Color Mix, Gabor, $LBP_{16,2}$, Fractals	94.20
4	$CLBP\_SMC_{24,5}$, Color Lab, Gabor, $LBP_{8,2}$	94.20
8	$CLBP\_SMC_{8,1}$, $CLBP\_SMC_{24,5}$, Color RGB, Color Lab, Color Mix, Gabor, $LBP_{16,2}$, Fractals	94.13

Table 7 Performance of the best ensembles using $n = 25$

Number of classifiers	Feature sets	Rec. rate %
6	$CLBP\_SMC_{16,3}$, $CLBP\_SMC_{24,5}$, Color RGB, Gabor, $LBP_{8,2}$, Fractals	97.77
4	$CLBP\_SMC_{16,3}$, $CLBP\_SMC_{24,5}$, Color RGB, $LBP_{8,2}$	97.71
4	$CLBP\_SMC_{24,5}$, Color RGB, Gabor, $LBP_{8,2}$	97.64
6	$CLBP\_SMC_{16,3}$, $CLBP\_SMC_{24,5}$, Color RGB, $LBP_{8,1}$, $LBP_{8,2}$, Fractals	97.64
6	$CLBP\_SMC_{16,3}$, $CLBP\_SMC_{24,5}$, Color RGB, Gabor, $LBP_{8,1}$, $LBP_{8,2}$, Fractals	97.64

divide-and-conquer strategy

sub-images + multi-feature sets + SVM

result: 97.77%

3. My work

a. SURF (Speeded-Up Robust Features) + BOW (bag of words) + SVM (Support Vector Machine)

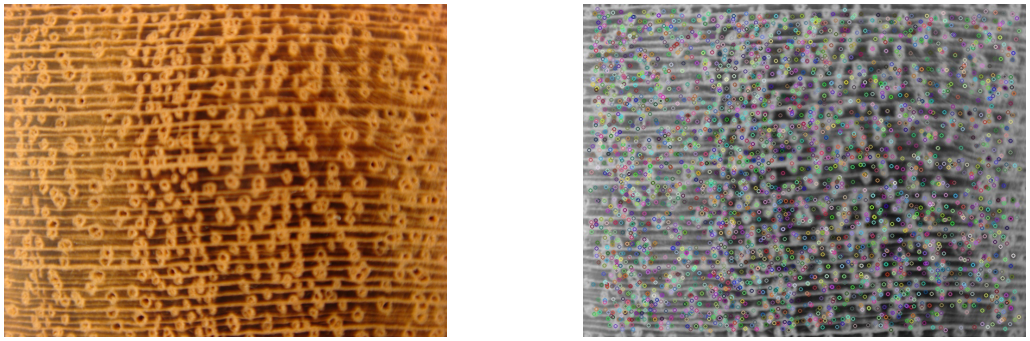


Fig.6 NUMBER 18: FOUND 3519 keypoints on the image. SURF run time: 612.078 ms

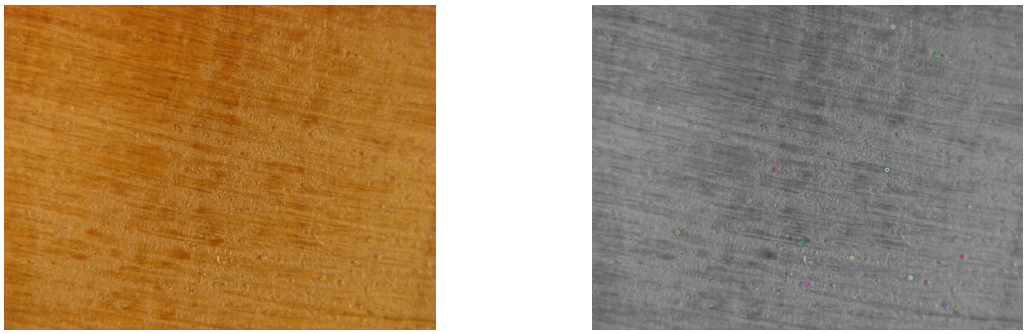


Fig.7 NUMBER 06: FOUND 26 keypoints on first image. SURF run time: 130.84 ms

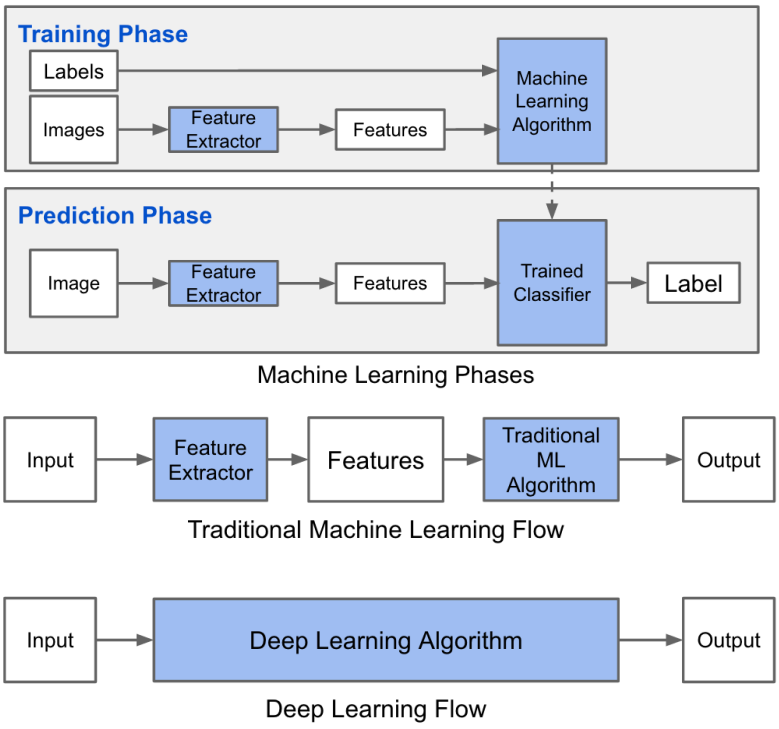
5 classes: best score ~98%

The accuracy decreases to 60~70% for 10 classes. Time-consuming

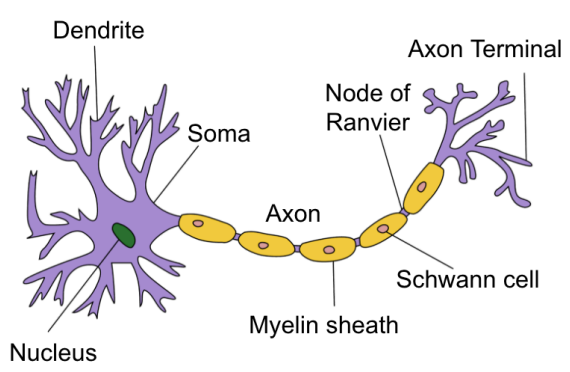
“Forest species recognition based on dynamic classifier selection and dissimilarity feature vector representation”, J. G. Martins, L. S. Oliveira, A. S. Britto Jr (2015).

They present 89.14% of accuracy using SURF as feature extractor for 2240 microscopic images from 112 different forest species.

b. Train convolutional neural network from scratch

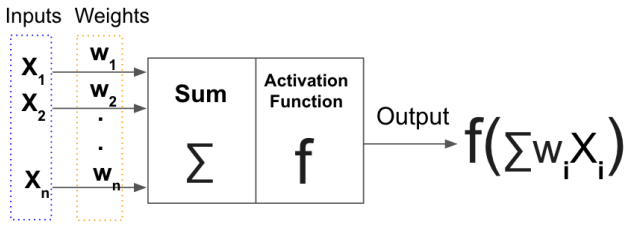


Machine learning Phase by @AdilMouja

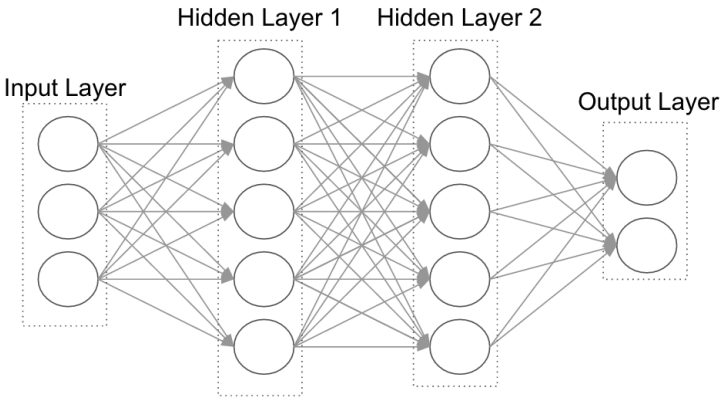


Structure of a typical neuron

(source: Wikipedia)



Structure of artificial neuron



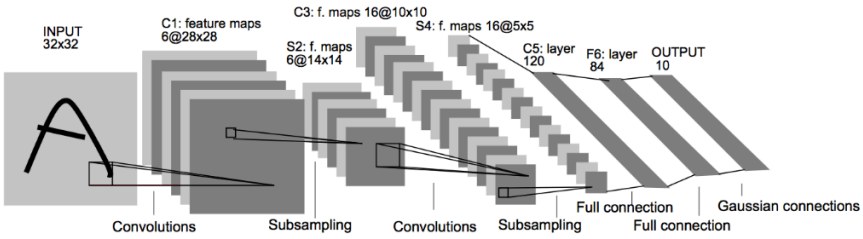
Feedforward neural network with 2 hidden layers

The goal of training Artificial Neural Network is to learn the network's weights. Needs:

1. Training data
2. Loss function: A function that measure the inaccuracy of predictions.

Algorithm: back propagation with gradient descent

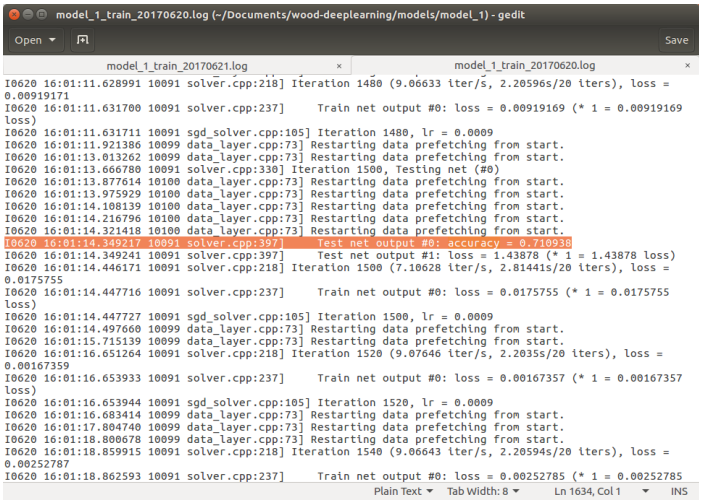
CONVOLUTIONAL NEURAL NETWORKS



CNN called LeNet by Yann LeCun (1998)

The simplest architecture of CNN starts with an input layer (images) followed by a sequence of convolutional layers and pooling layers, and ends with fully-connected layers.

For my experiment which is a classification task of 41-class dataset, I achieve accuracy=71.09% for validation test with a complex architecture contains 5 ConvNet layers.

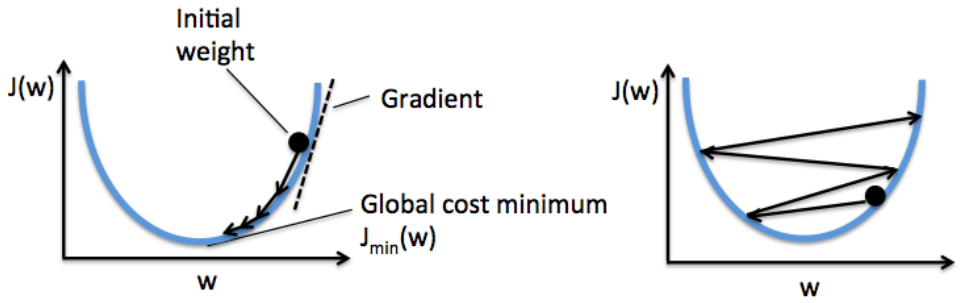


“Forest Species Recognition using Deep Convolutional Neural Networks”, L. G. Hafemann, L. S. Oliveira, P. Cavalin (2014)

The authors propose a CNN-based method achieves 95.77% of accuracy on the forest species dataset with macroscopic images.

c. Transfer learning

Objective function or Loss function or Cost function



It is an optimization problem that we need to minimize a loss function.

For machine learning, "*the objective function, averaged over all the training examples, can be seen as a kind of hilly landscape in the high-dimensional space of weight values*". ("Deep learning", Y. LeCun, Y. Bengio, G. Hinton)

Transfer Learning scenarios:

a. ConvNet as fixed feature extractor: Remove the last fully-connected layer

b. Fine-tuning the ConvNet:

"The second strategy is to not only replace and retrain the classifier on top of the ConvNet on the new dataset, but to also fine-tune the weights of the pretrained network by continuing the backpropagation. " (cs231n)

Pre-trained convolutional neural network on ImageNet + fine-tuning the parameters on my target dataset + sub-images + majority voting = 96.03% of accuracy