Deep Learning for Medical Image Segmentation & Classification

Dr. Arna Fariza, S.Kom., M.Kom

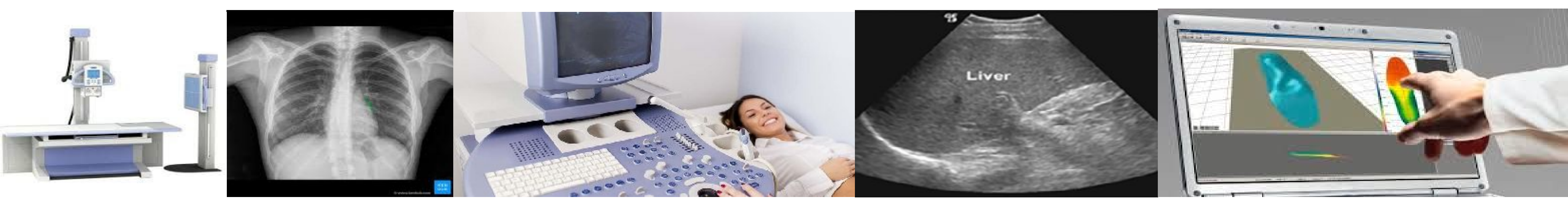
Webinar Medical Engineering

Program Pasca Sarjana

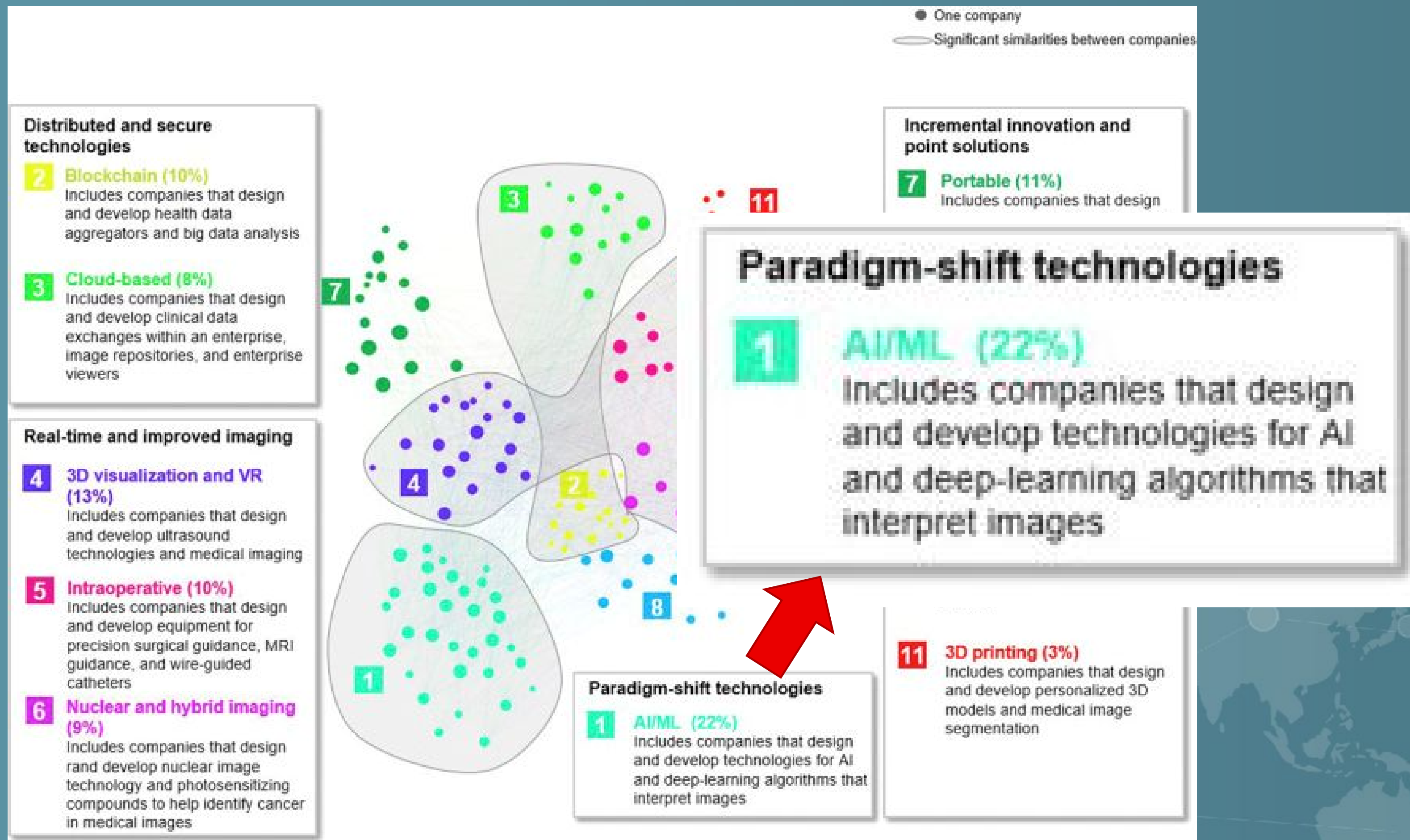
Politeknik Elektronika Negeri Surabaya

Background

- The discovery of X-ray in 1895 initiated the era of medical imaging diagnostics.
- Significant development in medical imaging technologies, processing medical images pose a substantial challenge by the implementation of digital medical image processing.
- Improve medical practice and refine health care systems all over the world
- Early detection of diseases
- Support accurate diagnosis and develop automated computer-aided diagnosis systems (CADs).



CLUSTER MAPPING FOR MEDICAL IMAGING

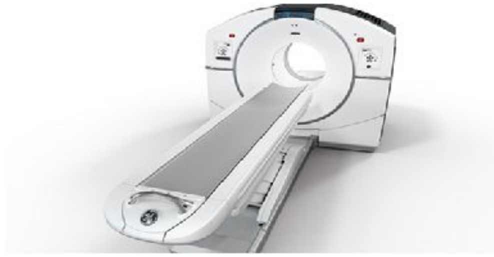


McKinsey analysis (McKinsey & Company, New York, New York) , S&P Capital IQ (New York, New York), and PitchBook Data Inc (Seattle, Washington)

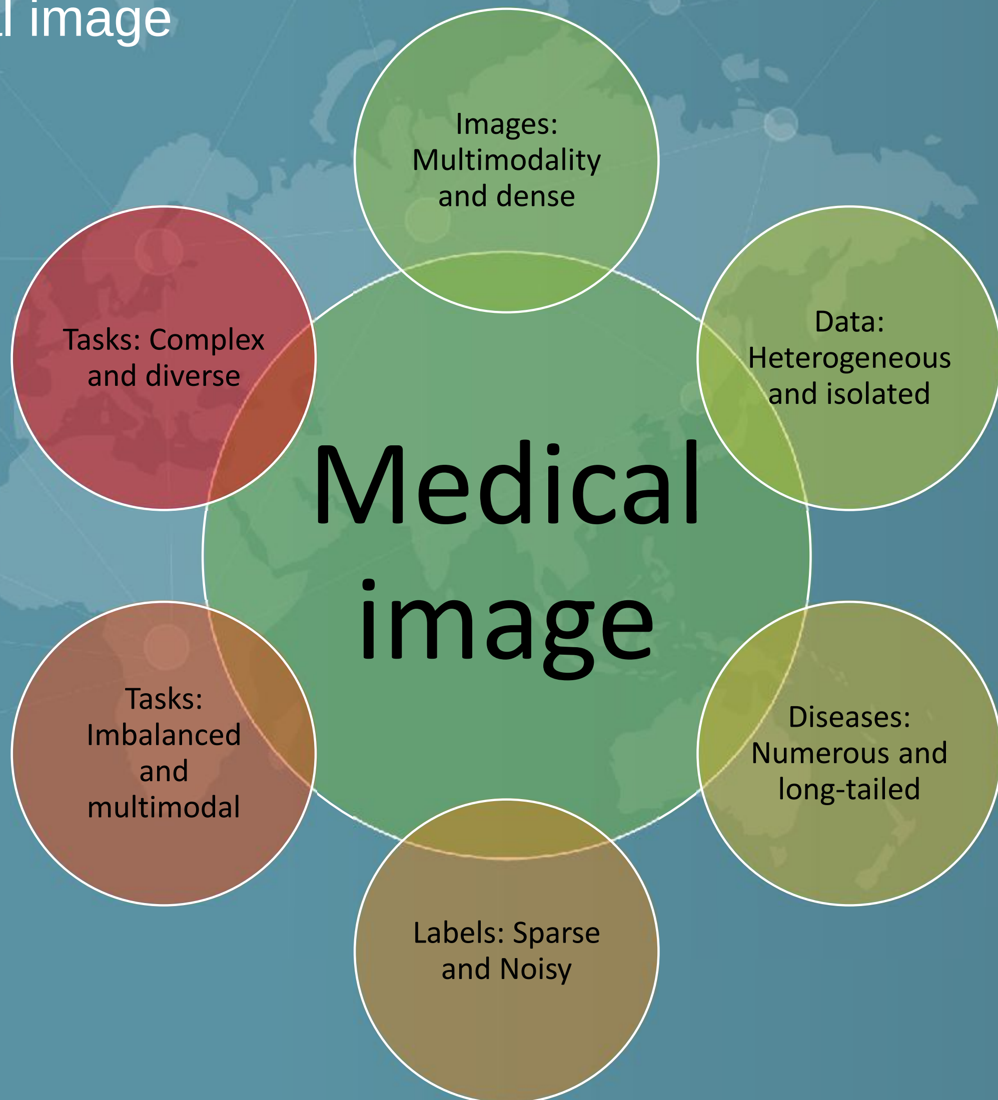
Medical imaging

- Electromagnetic radiation, radioactivity, nuclear magnetic resonance, and sound to generate visual representations or images of internal tissues of the human body or a part of the human body in a non-invasive manner.
- X-ray radiography, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound (US) for about 90% of all healthcare data
- Most of the medical images have noise, intensity inhomogeneity, and weak boundaries, which require complex procedures

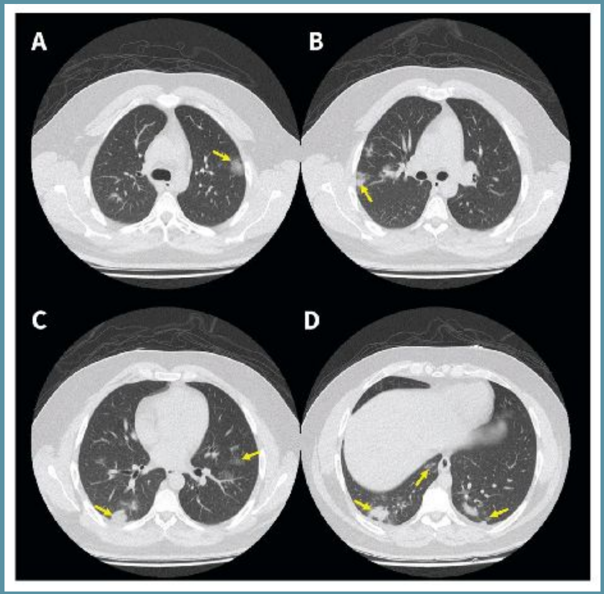




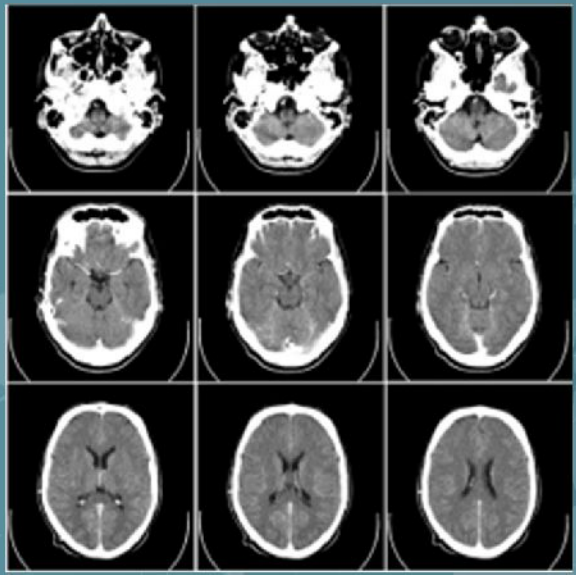

Main traits of Medical image (Kevin Zhou 2020)



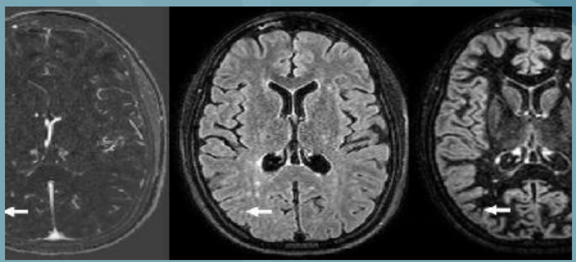
CT Image



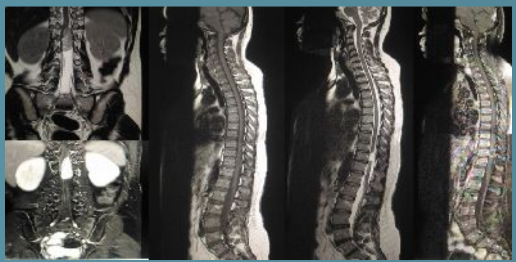
Chest CT Image


Brain CT Image

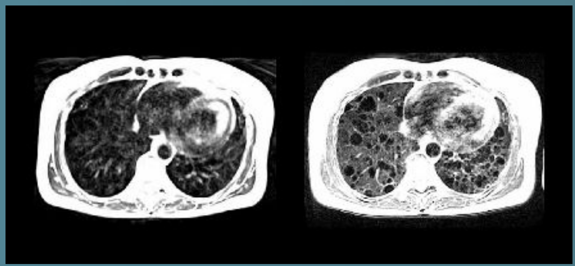
MRI Image



Brain MRI

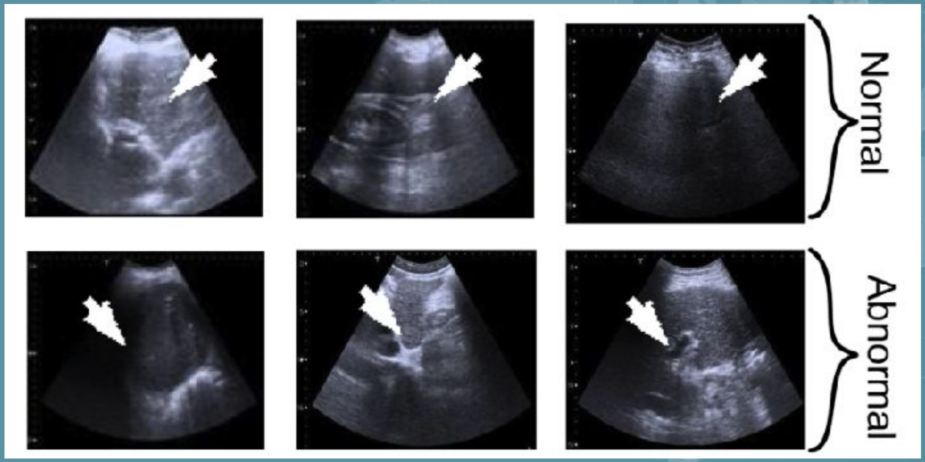


Whole-Body MRI

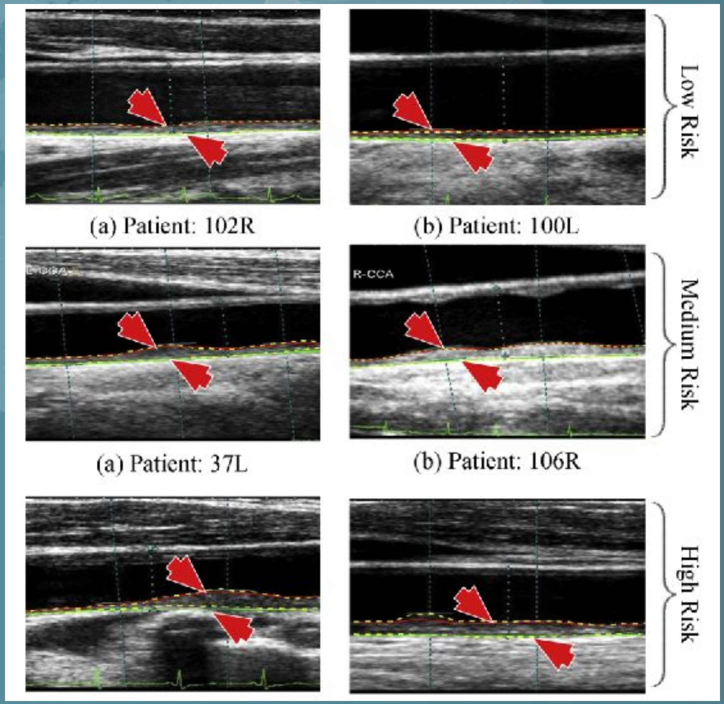


Lung cysts

Ultrasound Image

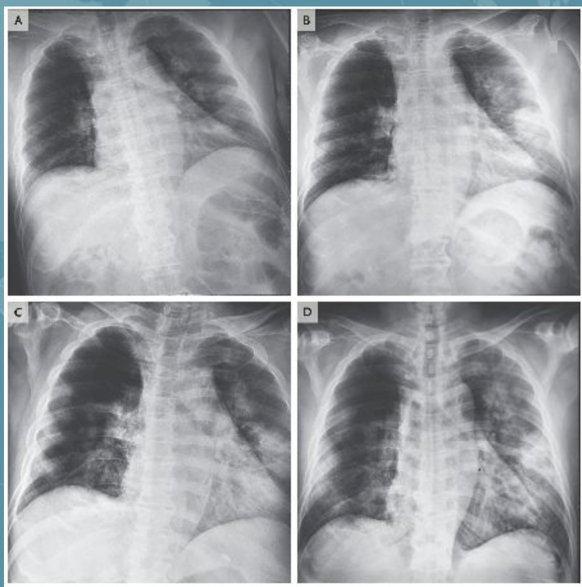


Liver Disease images



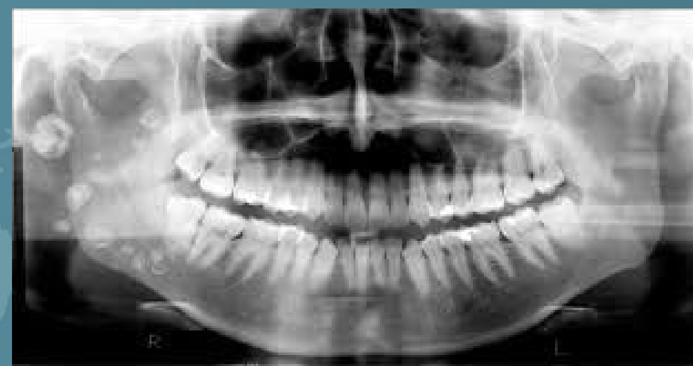
Carotid artery

X-ray Image



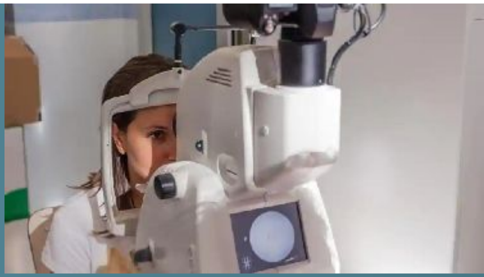
Chest X-ray

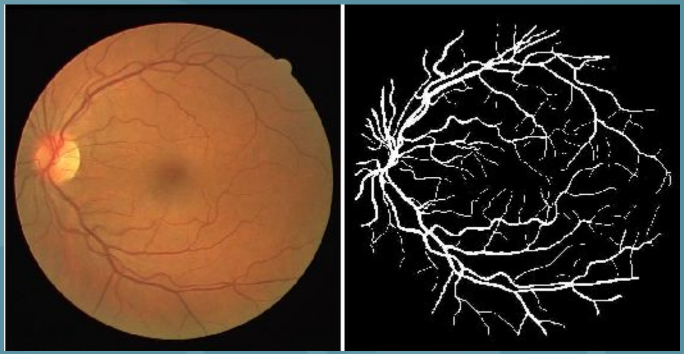
Bone X-ray



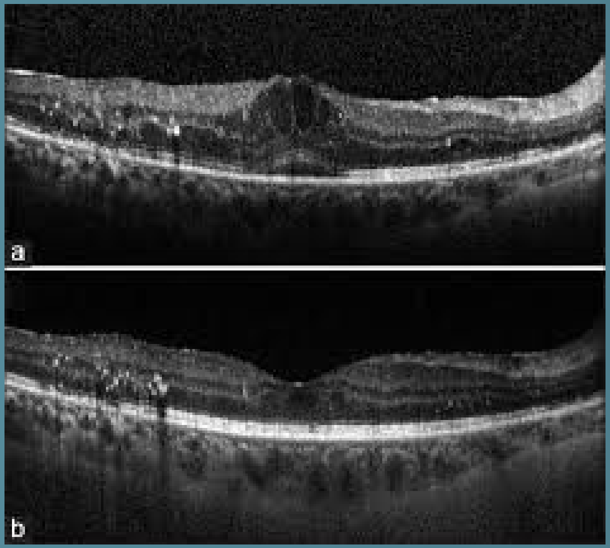
Panoramic radiography

Optical Coherence Tomography





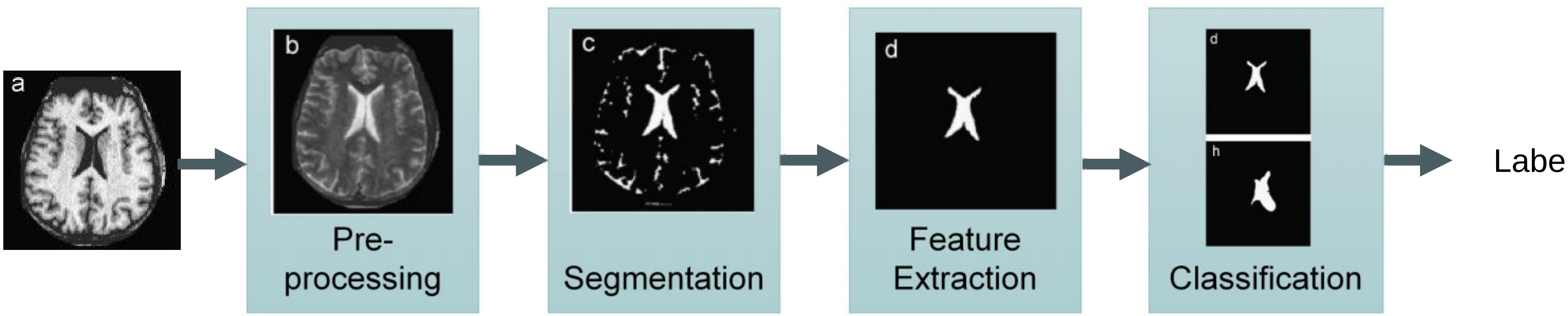
Retinal Blood Vessel



Diabetic Retinopathy

Cone-Beam Computed Tomography (CBCT)

Medical Images Acquisition



Minimize the noise, artifacts and bias effects; improving the contrast

Partitioning an image into meaningful parts, often consisting of an object and background

Extract features according to size and structure, texture and color

assign one or more labels to an image

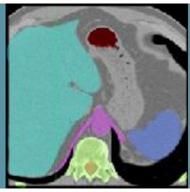
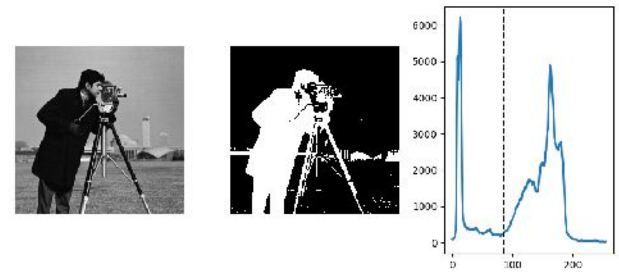


Image Segmentation

- Image Segmentation: extracts the region of interest (ROI) through an automatic or semiautomatic process
- Thresholding: Otsu
- Clustering : extracting the global characteristics of the image to professionally separate the ROI from the background
  - Hierarchical clustering, Divisive clustering, Mean shift clustering, K-Means, Fuzzy C-Means (FCM)
- Region-based:
  - Region merging, Region growing, Active contour
- Graph-cut methods: choosing seed points representing some pixels to belong to the object and other pixels from the background.
- Semi-automatic: user interaction is applied before segmentation process



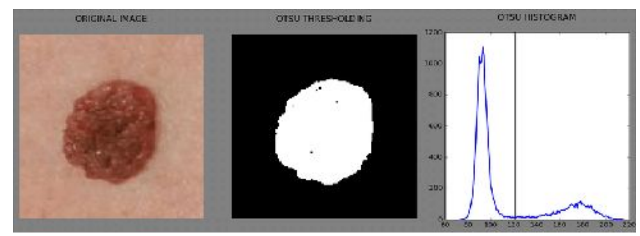
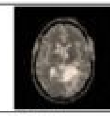
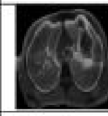
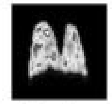
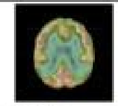
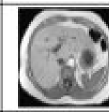
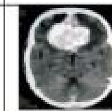


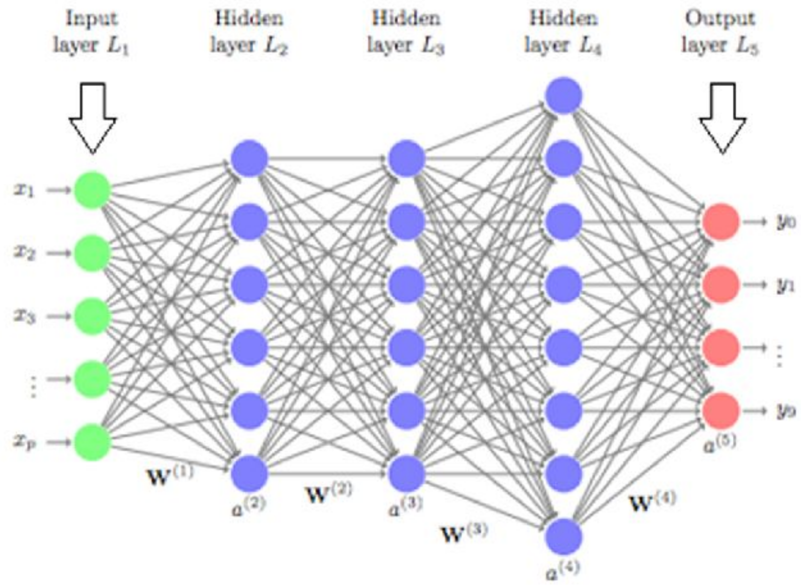
Image Classification

Fused Medical Image	I	II	III	IV	V	VI	VII
							
Class	Malignant	Benign	Benign	Malignant	Malignant	Malignant	Benign
Accuracy	92.22	96.22	98.41	89.56	96.58	92.1	93.89

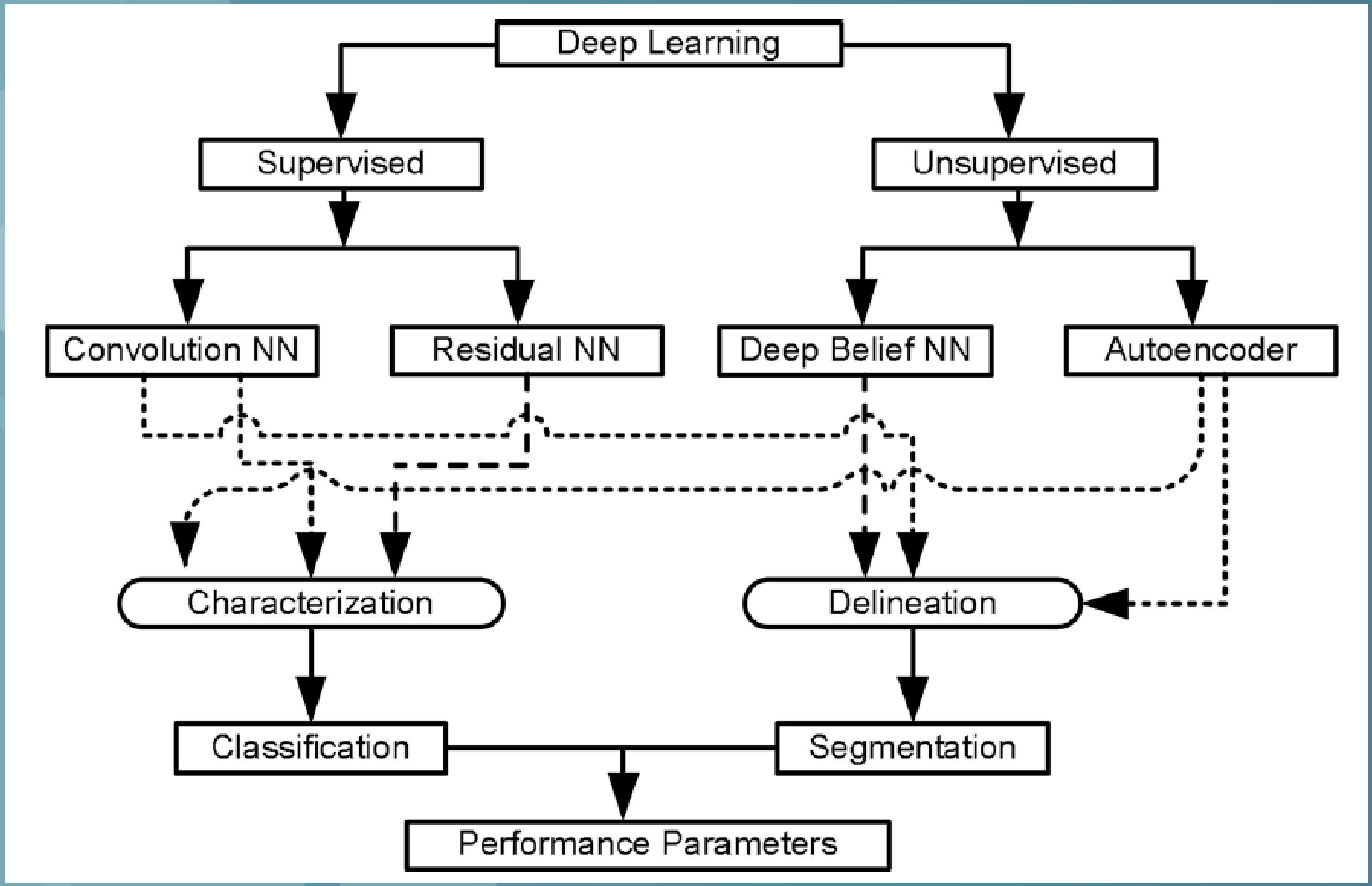
- Preceded by segmentation and feature extraction.
- Concerns the training of classification models on a training set
- Develops the classification of whole screen using the best performing classifier
- Statistical and classical:
  - Bayesian
  - Linear discriminant analysis
  - K-Nearest Neighbor
  - Support Vector Machine (SVM)
- Artificial Intelligent:
  - Neural Network
  - Fuzzy Logic
  - Decision Tree
  - Genetic Algorithm

DEEP LEARNING

- Worldwide interest in artificial intelligence (AI) applications, including imaging, is high and growing rapidly
- Availability of large datasets ("big data")
- Substantial advances in computing power
- Success measured: increased diagnostic certainty, faster turnaround, better outcomes for patients, and better quality of work life for observer (doctor/radiologist)

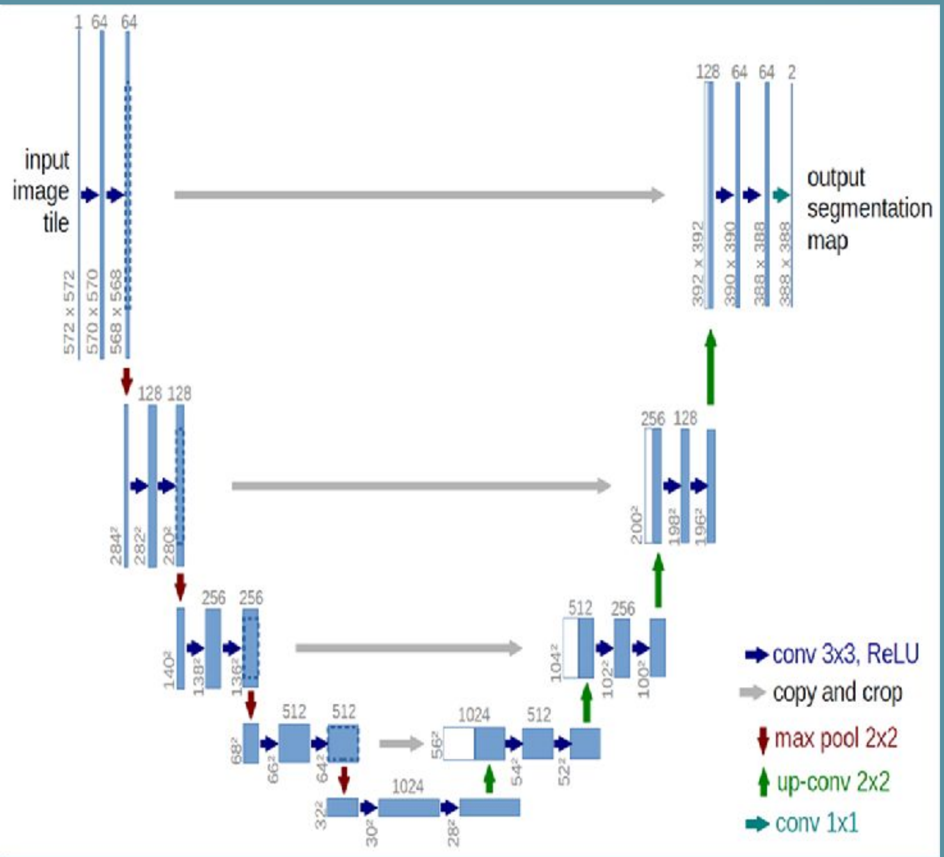


DL for Medical Image



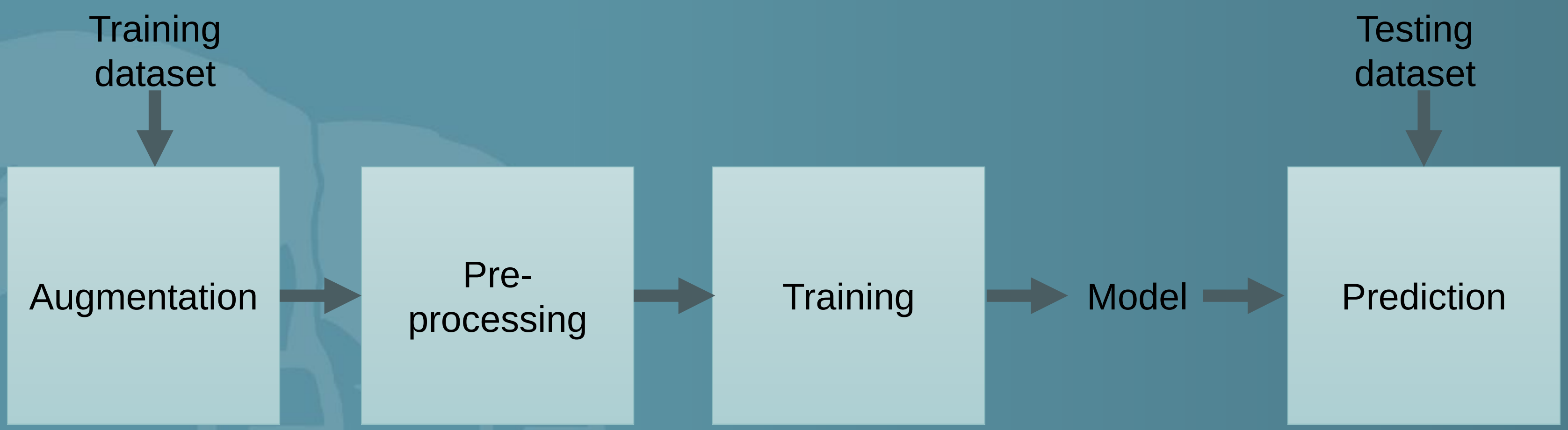
Source: Saba et al. 2019

Segmentation using U-NET (Ronneberger et al., 2015)

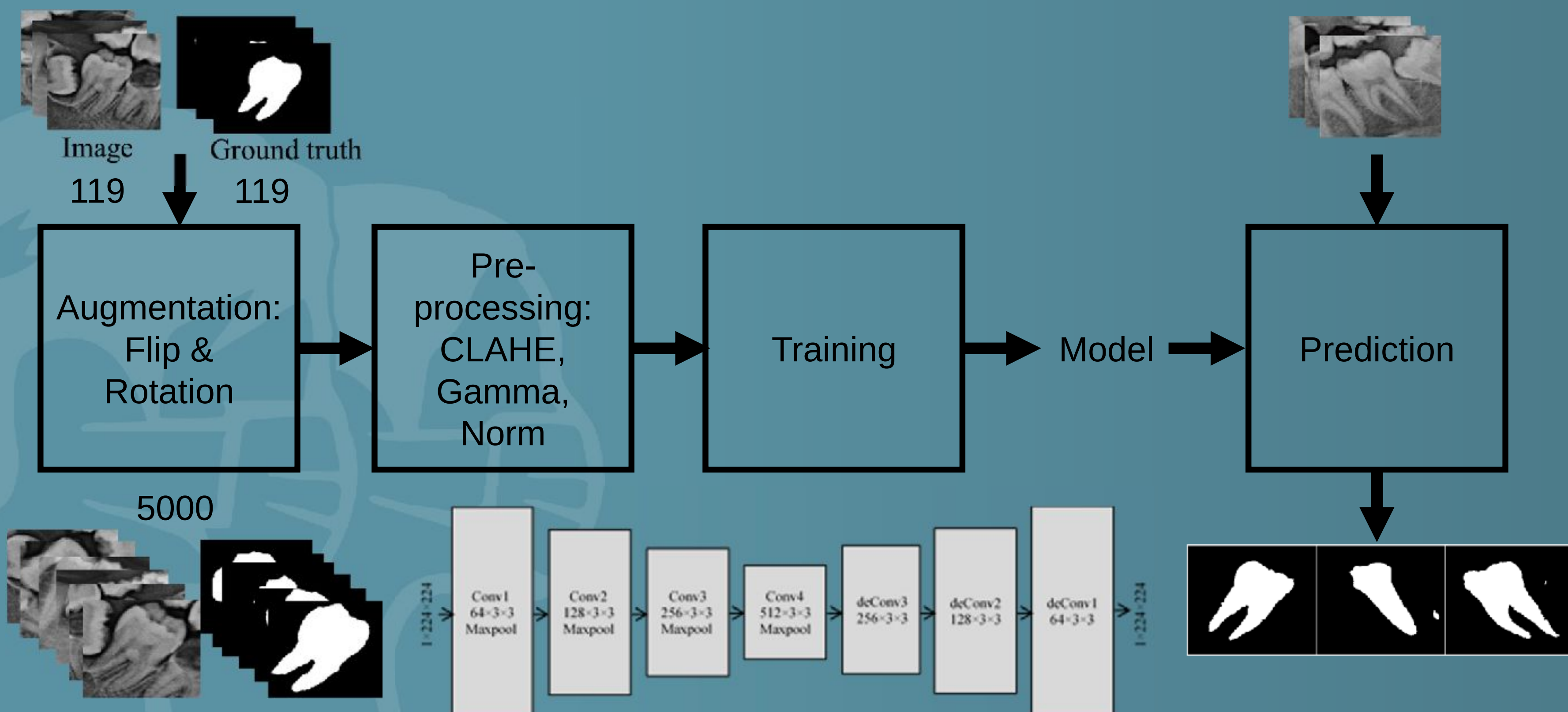


- In biomedical image processing, the desired output should include localization, i.e., a class label is supposed to be assigned to each pixel
- It consists of a contracting path / down sampling (left side) and an expansive path / up sampling (right side)
- Contracting path: two 3x3 convolutions, ReLU, a 2x2 max pooling
- Expansive path: up sampling of the feature map, 2x2 convolution concatenation with the correspondingly cropped feature map from the contracting path, two 3x3 convolutions, ReLU.

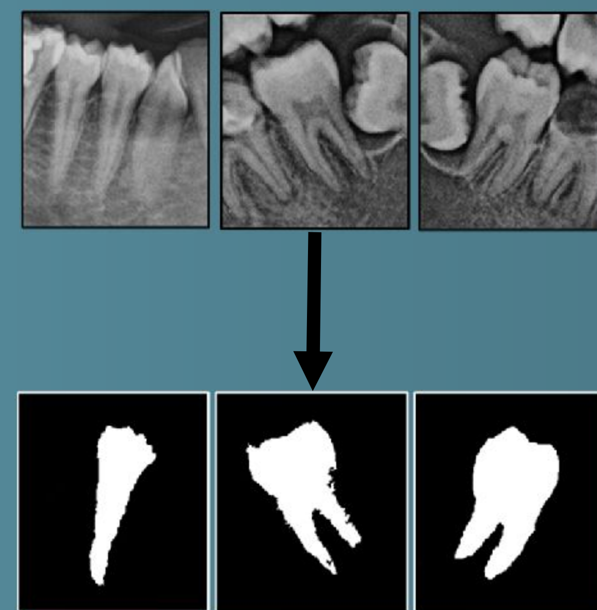
Methodology of Medical Image Segmentation & Classification



Dental X-ray Segmentation using U-NET



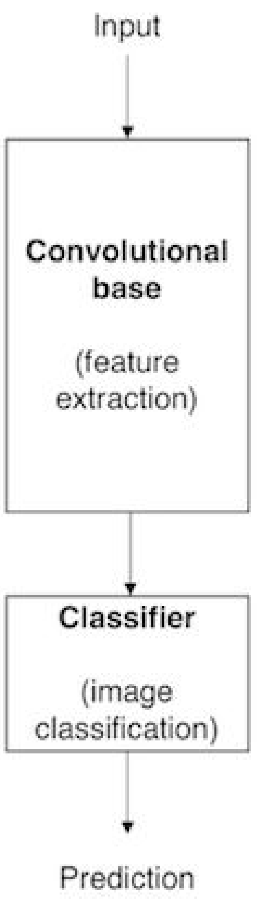
Dental X-ray Segmentation using UNET

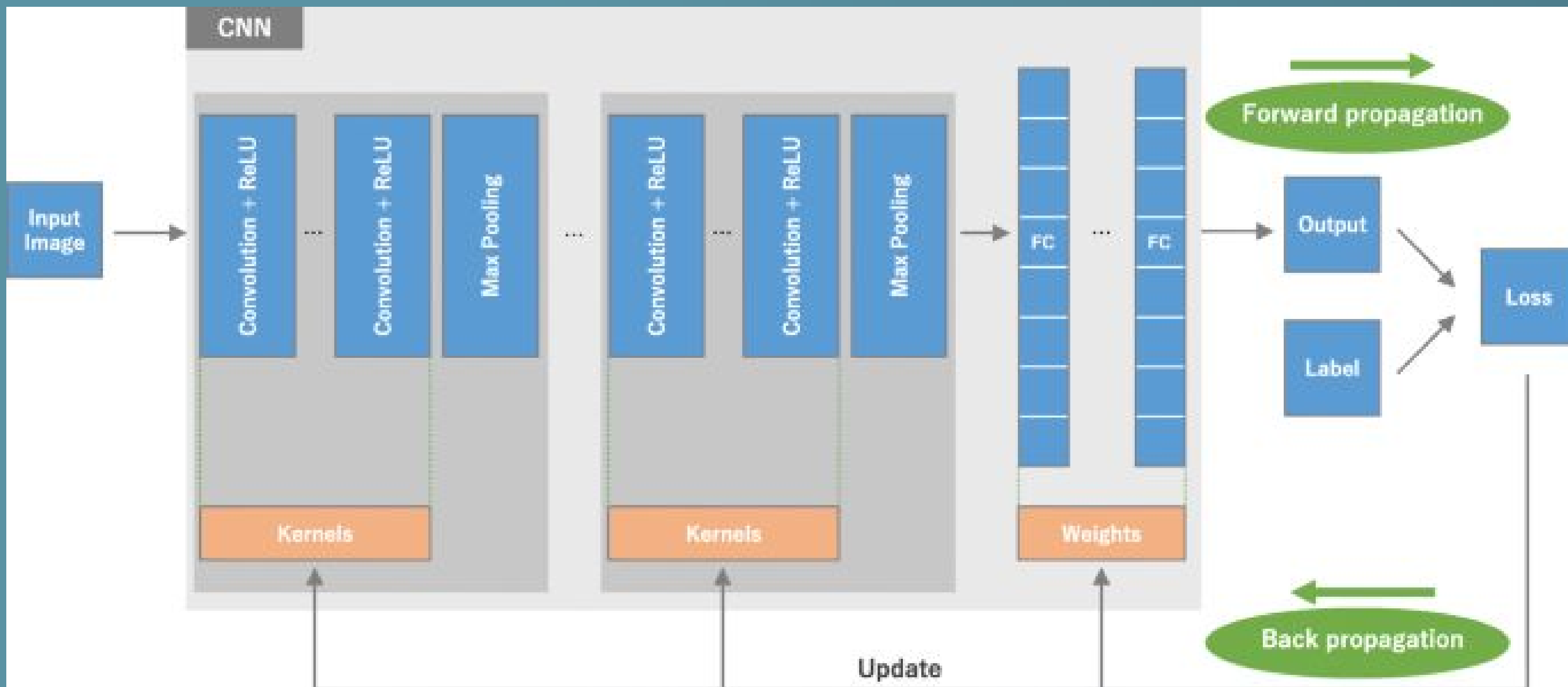


- Requires ground truth for the training process
- The amount of data is relatively small, with augmentation will effectively produce superior segmentation

Convolutional Neural Network

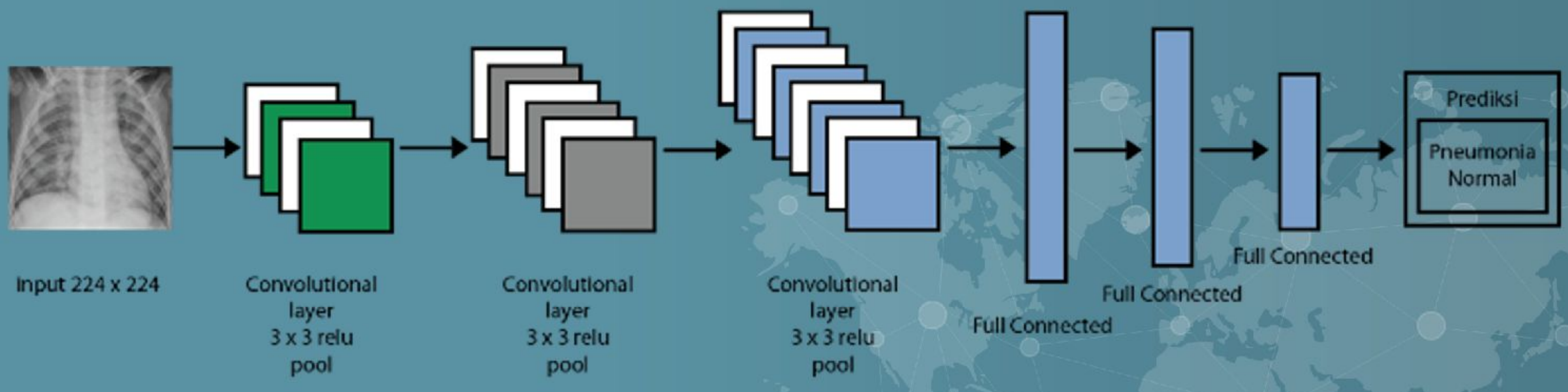
- In traditional image classification, low-level or mid-level features are extracted to represent the image and a trainable classifier is then used for label assignments.
- The high-level feature representation of deep convolutional neural networks has proven to be superior to hand-crafted low-level and mid-level features.
- In the deep convolutional neural network, both feature extraction and classification networks are combined together and trained end-to-end.
- Convolution: to generate features from the image.
- Classifier: to classify the image based on the detected features.





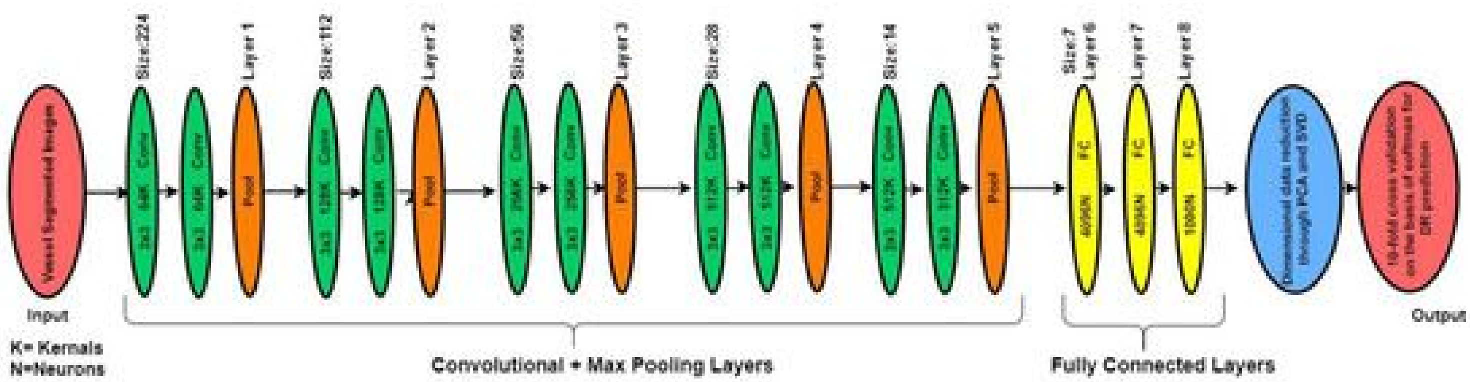
Source: Yamashita et al., 2018

CNN Architecture



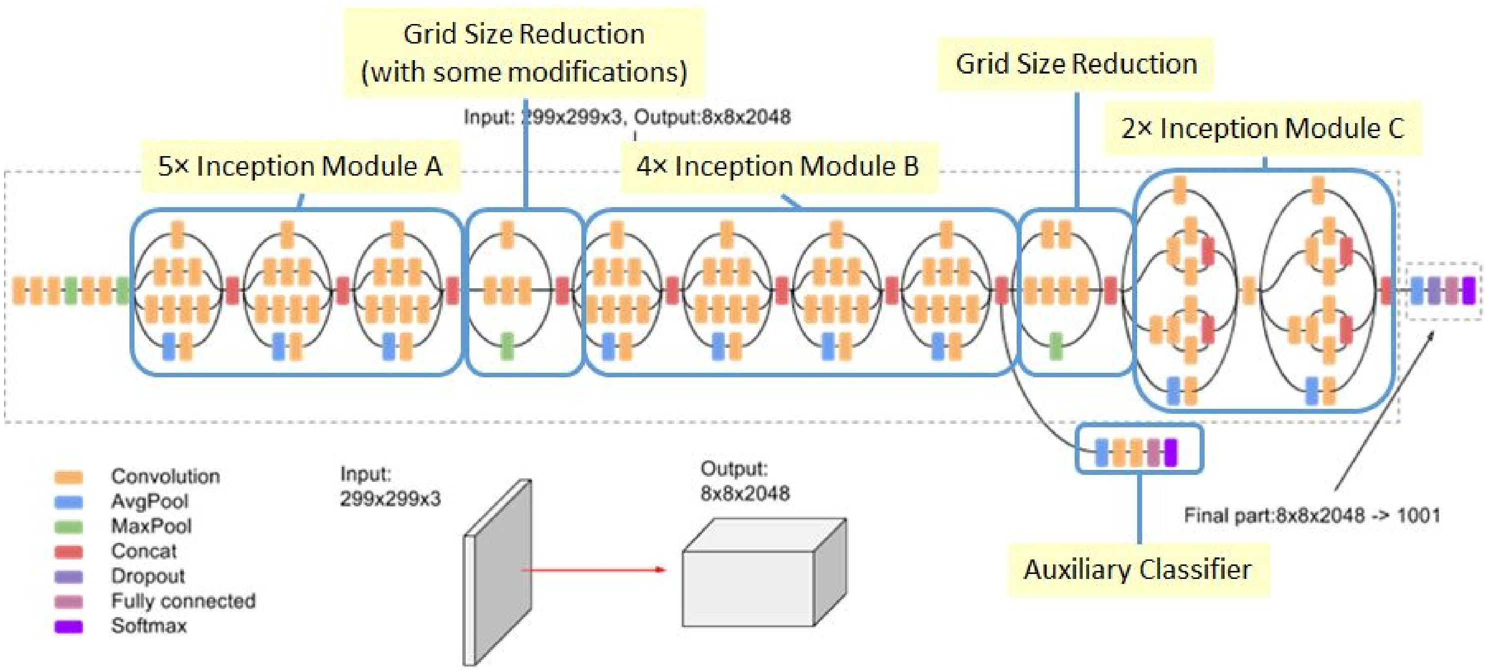
CNN Medical Image Research

- Mateen, M., Wen, J., Song, S., & Huang, Z. (2019). Fundus image classification using VGG-19 architecture with PCA and SVD. *Symmetry*, *11*(1), 1.



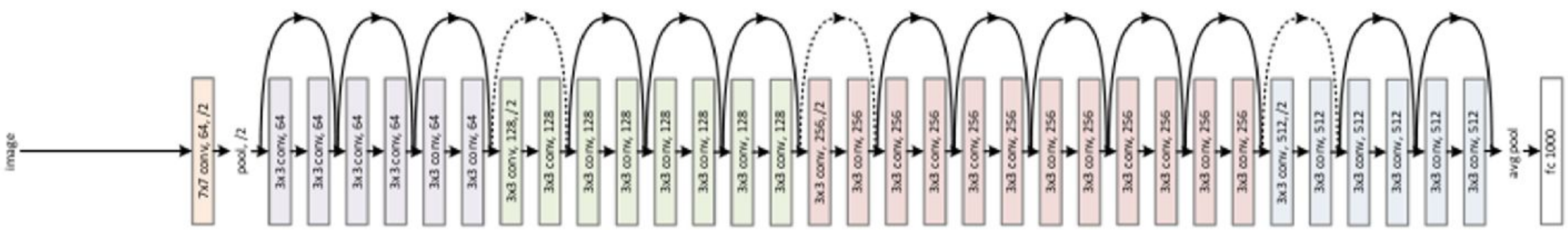
CNN Medical Image Research

Chang, J., Yu, J., Han, T., Chang, H. J., & Park, E. (2017, October). A method for classifying medical images using transfer learning: A pilot study on histopathology of breast cancer. In *2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom)* (pp. 1-4). IEEE.

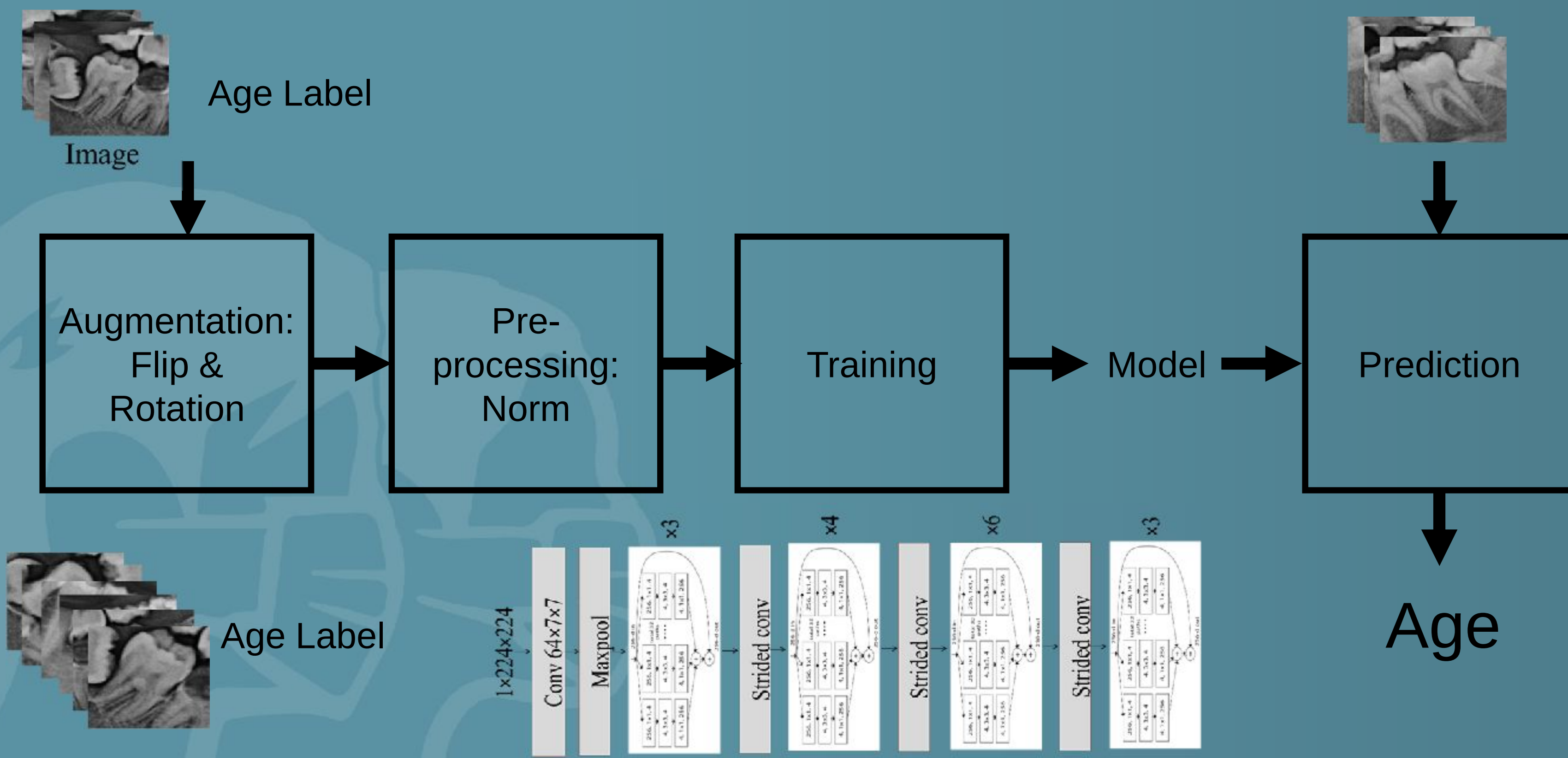


CNN Medical Image Research

Reddy, A. S. B., & Juliet, D. S. (2019, April). Transfer Learning with ResNet-50 for Malaria Cell-Image Classification. In *2019 International Conference on Communication and Signal Processing (ICCSP)* (pp. 0945-0949). IEEE.

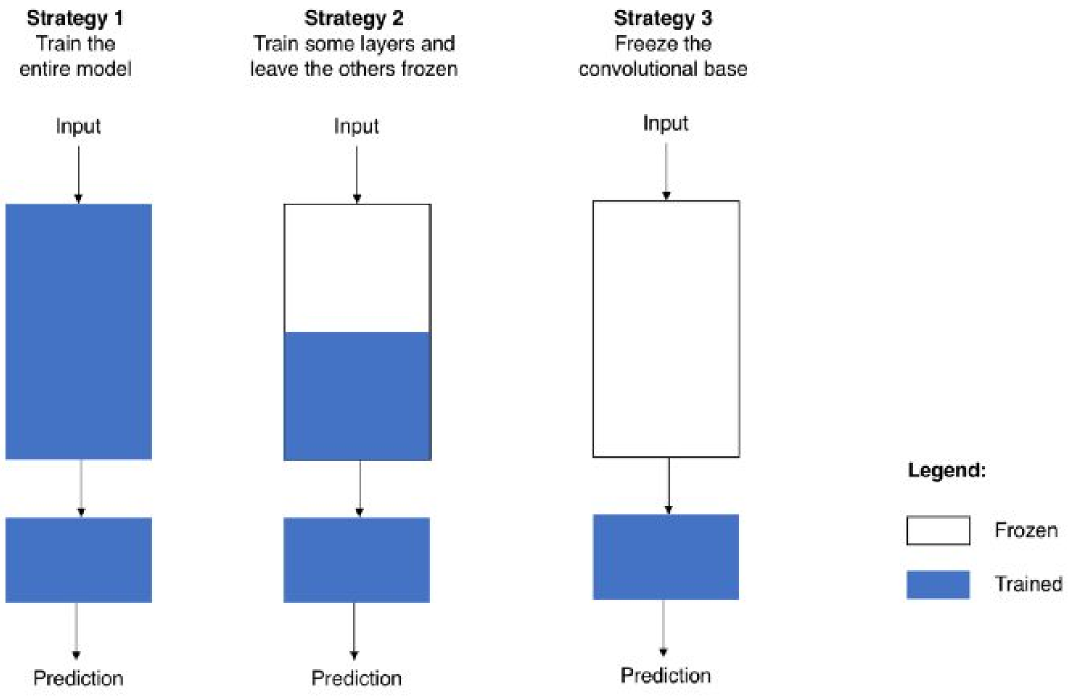


Dental X-ray Classification using CNN



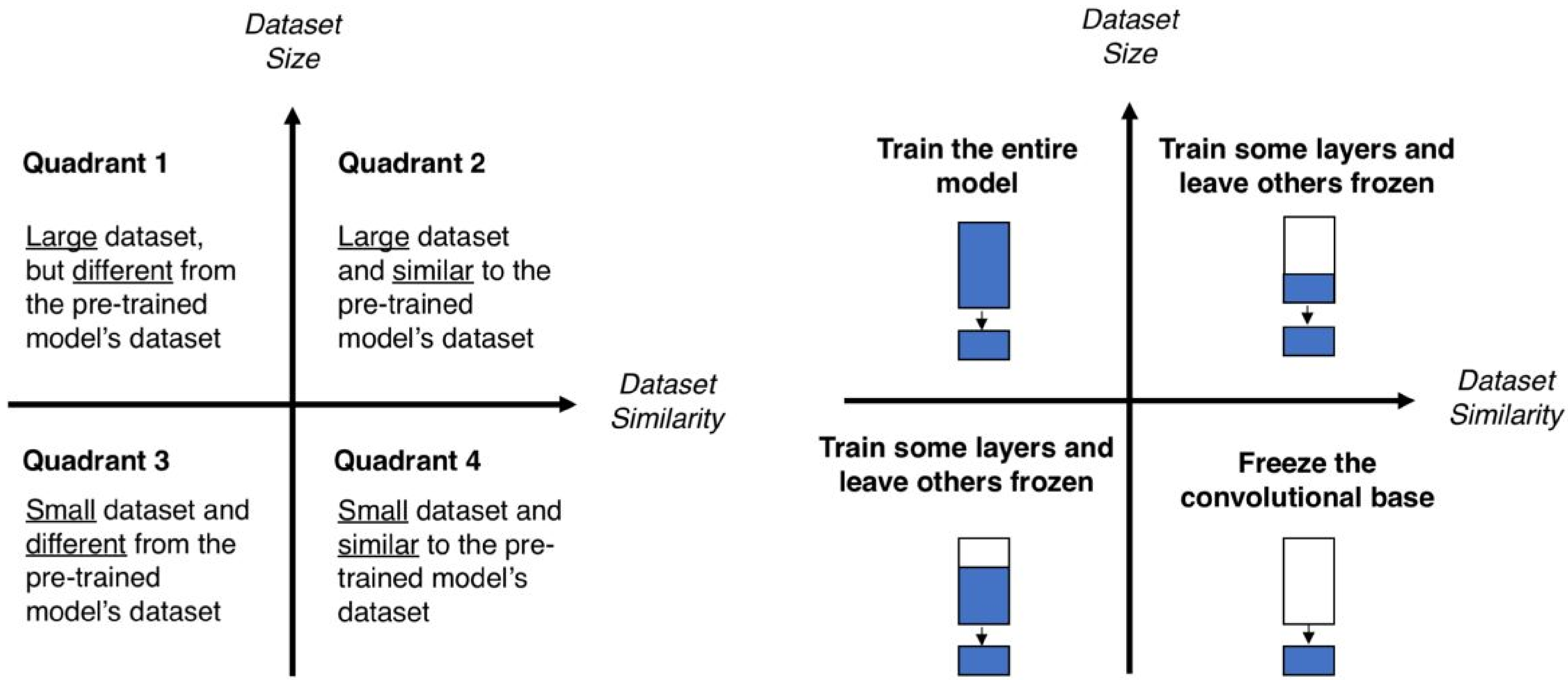
Transfer Learning

- Transfer learning is a popular method in computer vision because it allows us to **build accurate models in a timesaving way** (Rawat & Wang 2017).
- transfer learning is usually expressed through the use of **pre-trained models**.
- A pre-trained model is a model that was trained on a large benchmark dataset to solve a problem similar to the one that we want to solve.
- Fine-tune strategies:
  1. Train the entire model
  2. Train some layers and leave the others frozen
  3. Freeze the convolutional base



Source: Pedro Marcelino Transfer learning from pre-trained models

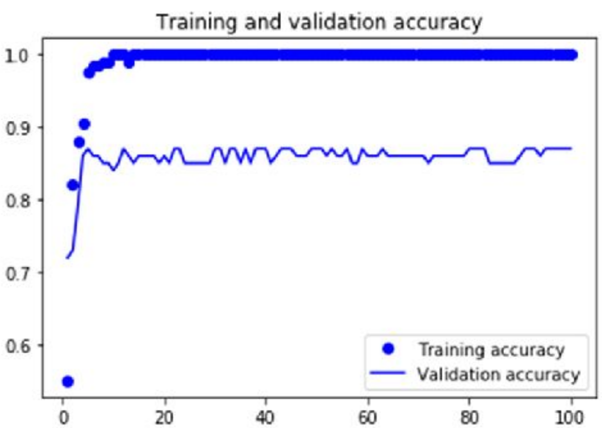
Fine-tune Model

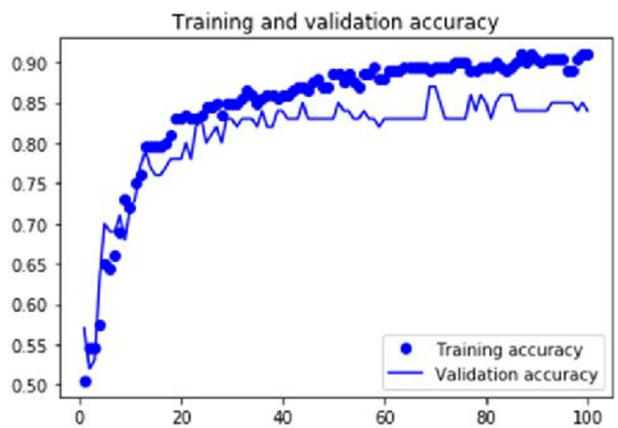


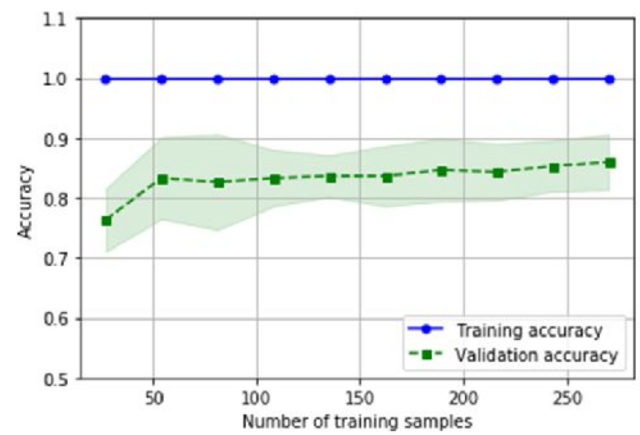
Source: Pedro Marcelino Transfer learning from pre-trained models

Classifier

1. **Fully-connected layers.** Use a stack of fully-connected layers followed by a softmax activated layer (Krizhevsky et al. 2012, Simonyan & Zisserman 2014, Zeiler & Fergus 2014).
2. **Global average pooling.** Instead of adding fully connected layers on top of the convolutional base, add a global average pooling layer and feed its output directly into the softmax activated layer (Lin et al. 2013)
3. **Linear support vector machines.** training a linear SVM classifier on the features extracted by the convolutional base (Tang 2013)

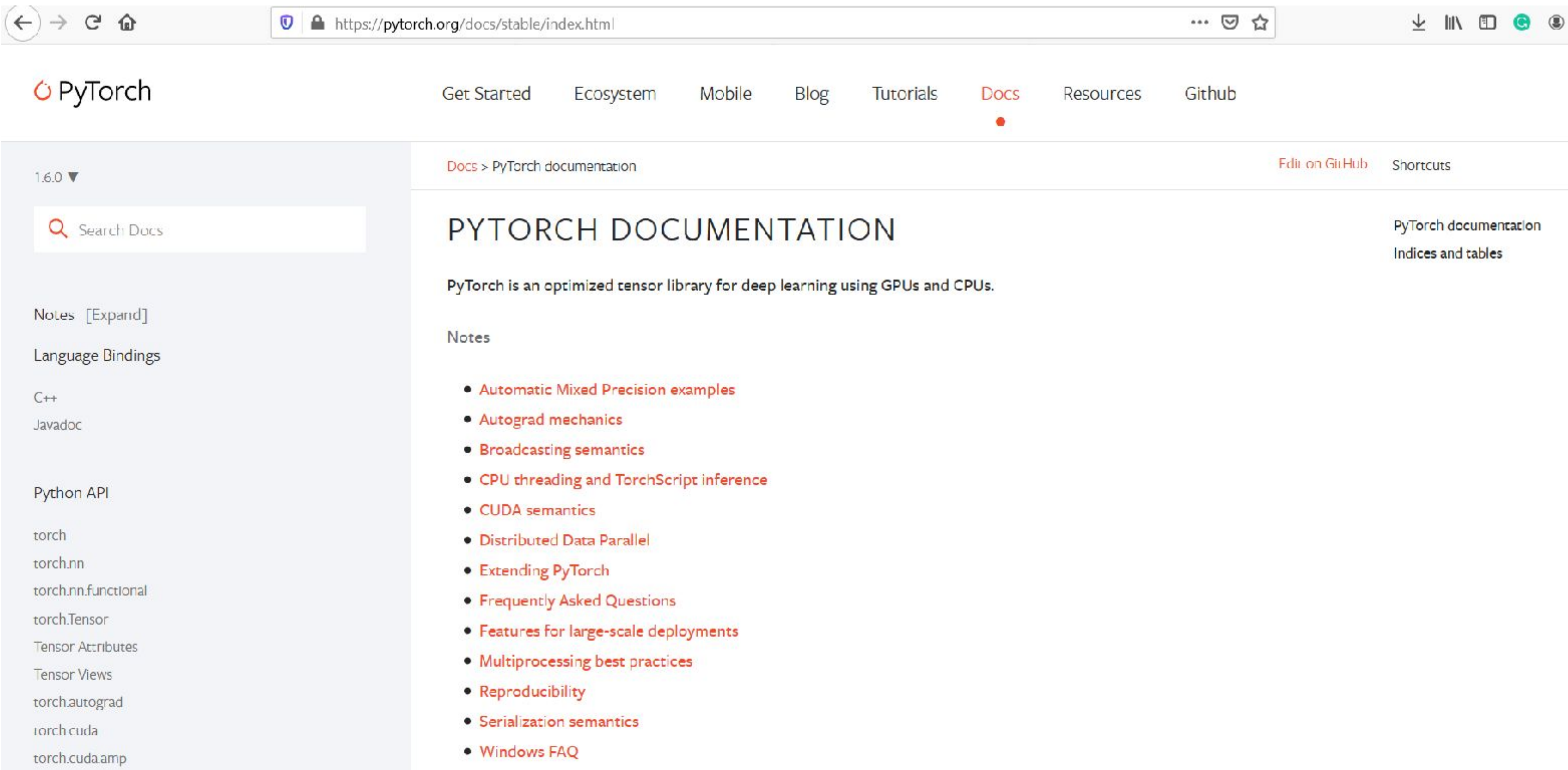






Source: Pedro Marcelino Transfer learning from pre-trained models

Pytorch Documentation



Pytorch Documentation

PyTorch

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Notes [Expand]

Language Bindings

C++

Javadoc

Python API

torch

torch.nn

torch.nn.functional

torch.Tensor

Tensor Attributes

Tensor Views

torch.autograd

torch.cuda

torch.cuda.amp

torch.distributed

torch.distributions

torch.futures

Docs > torchvision > torchvision.models

TORCHVISION.MODELS

The models subpackage contains definitions of models for addressing different tasks, including: image classification, pixelwise semantic segmentation, object detection, instance segmentation, person keypoint detection and video classification.

Classification

The models subpackage contains definitions for the following model architectures for image classification:

- AlexNet
- VGG
- ResNet
- SqueezeNet
- DenseNet
- Inception v3
- GoogLeNet
- ShuffleNet v2
- MobileNet v2
- ResNeXt
- Wide ResNet
- MNASNet

You can construct a model with random weights by calling its constructor:

Pytorch Documentation

Language Bindings

- C++
- Javadoc

Python API

- torch
- torch.nn
- torch.nn.functional
- torch.Tensor
- Tensor Attributes
- Tensor Views
- torch.autograd
- torch.cuda
- torch.cuda.amp
- torch.distributed
- torch.distributions
- torch.futures
- torch.hub
- torch.jit
- torch.nn.init
- torch.onnx
- torch.optim
- Complex Numbers
- Quantization
- Distributed RPC Framework
- torch.random
- torch.sparse

Docs > torch.nn

Loss Functions

`nn.L1Loss`	Creates a criterion that measures the mean absolute error (MAE) between each element in the input x and target y .
`nn.MSELoss`	Creates a criterion that measures the mean squared error (squared L2 norm) between each element in the input x and target y .
`nn.CrossEntropyLoss`	This criterion combines `nn.LogSoftmax()` and `nn.NLLLoss()` in one single class.
`nn.CTCLoss`	The Connectionist Temporal Classification loss.
`nn.NLLLoss`	The negative log likelihood loss.
`nn.PoissonNLLLoss`	Negative log likelihood loss with Poisson distribution of target.
`nn.KLDivLoss`	The `Kullback-Leibler divergence`_ Loss
	Creates a criterion that measures the Binary Cross Entropy

On Going Research

- Age estimation based on face recognition
- Age estimation based on dental X-ray images
- Detection of Blindness disease on OCT Image
- Identification of Signature Validity
- Detection of the patient’s level of emergency based on facial expressions
- Age estimate based on X-ray images
- Panoramic radiography segmentation


THANK YOU