Overview of Machine Learning in Medical Imaging

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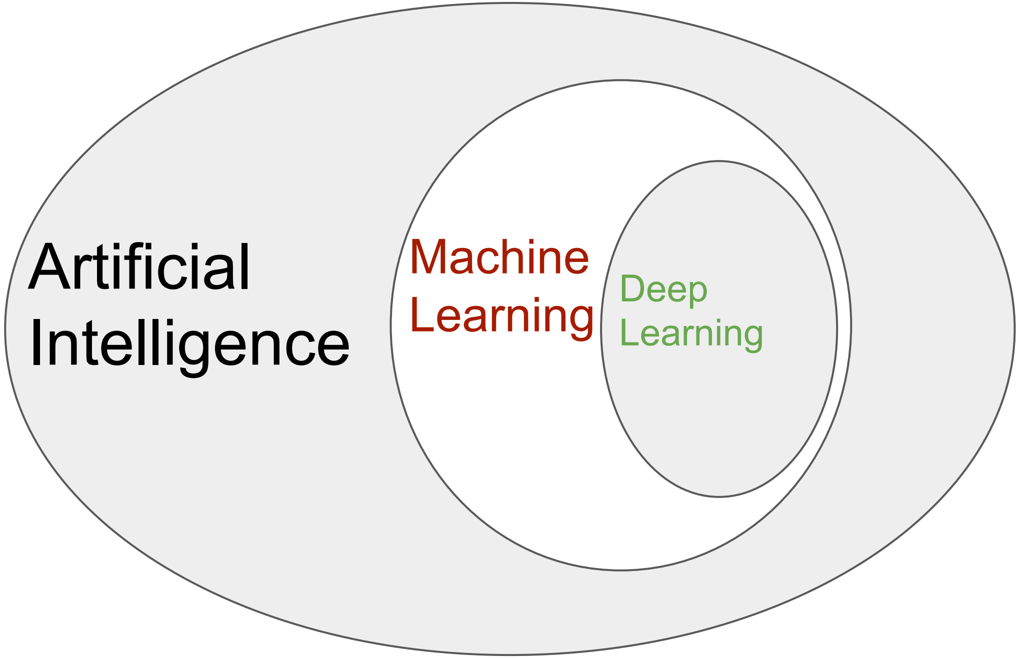
5th Annual Loma Linda Workshop

Machine Learning

Robotics
Speech Processing
Natural Language Processing
Data mining
Machine Learning
…

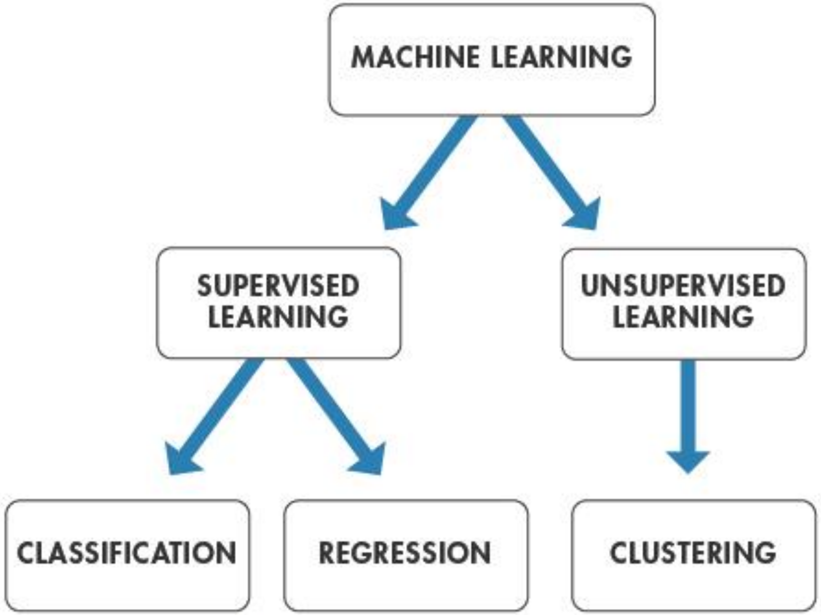


Deep Learning
Decision Trees
Clustering
Genetic Algorithms
….

Convolutional Neural Network
Recurrent Neural Network
...

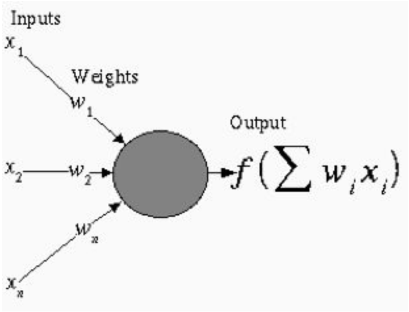
Machine Learning

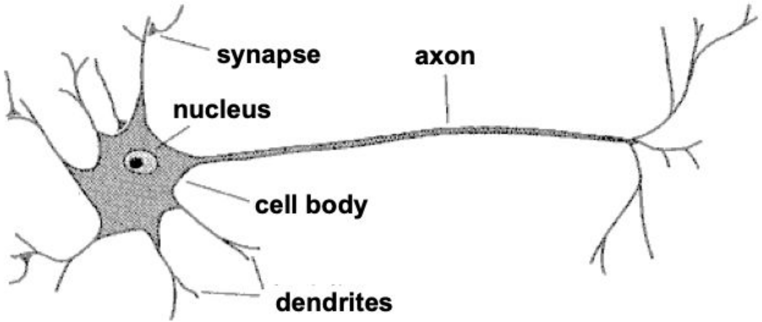
- Supervised
    - training data + desired inputs
- Unsupervised
    - training data
- Semi-supervised
    - training data + a few desired inputs
- Reinforcement
    - rewards from sequence of action

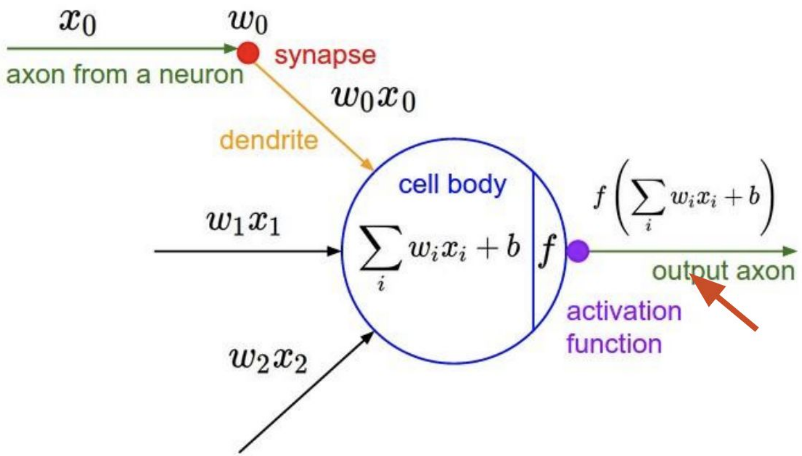


Neural Network

Perception

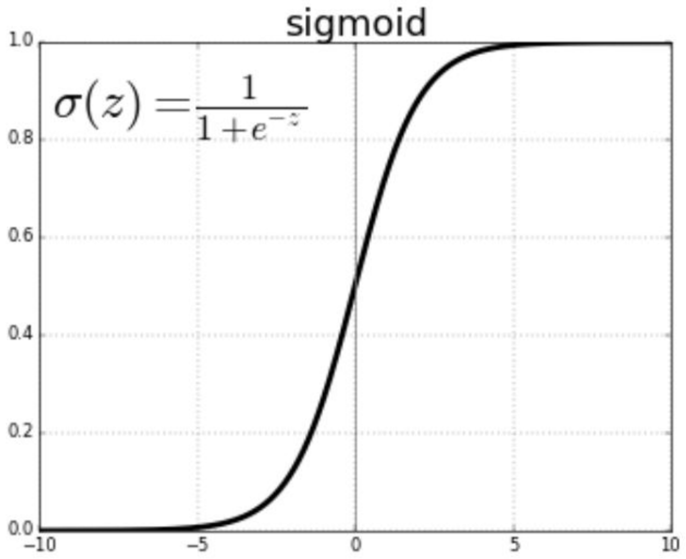


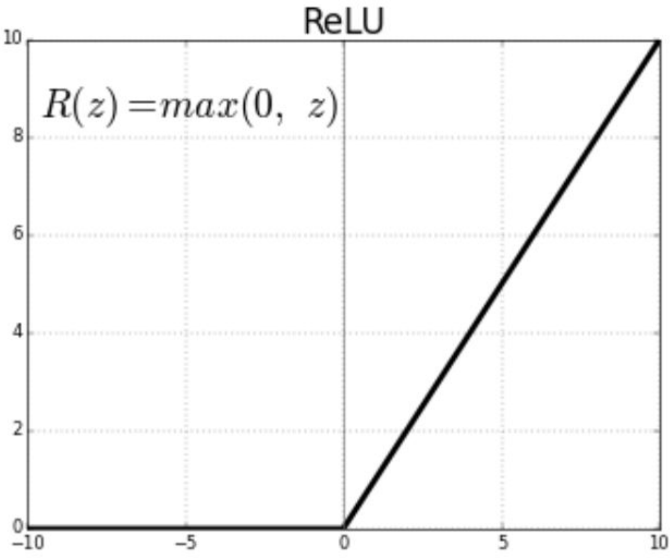




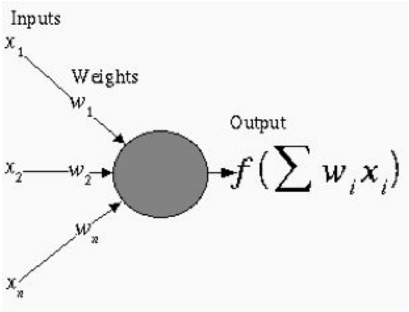
Neural Network

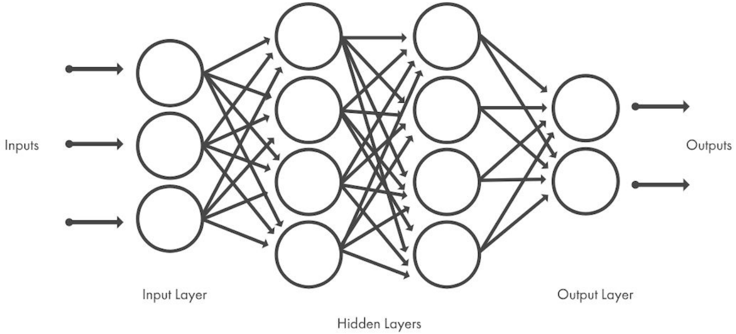
Activation functions





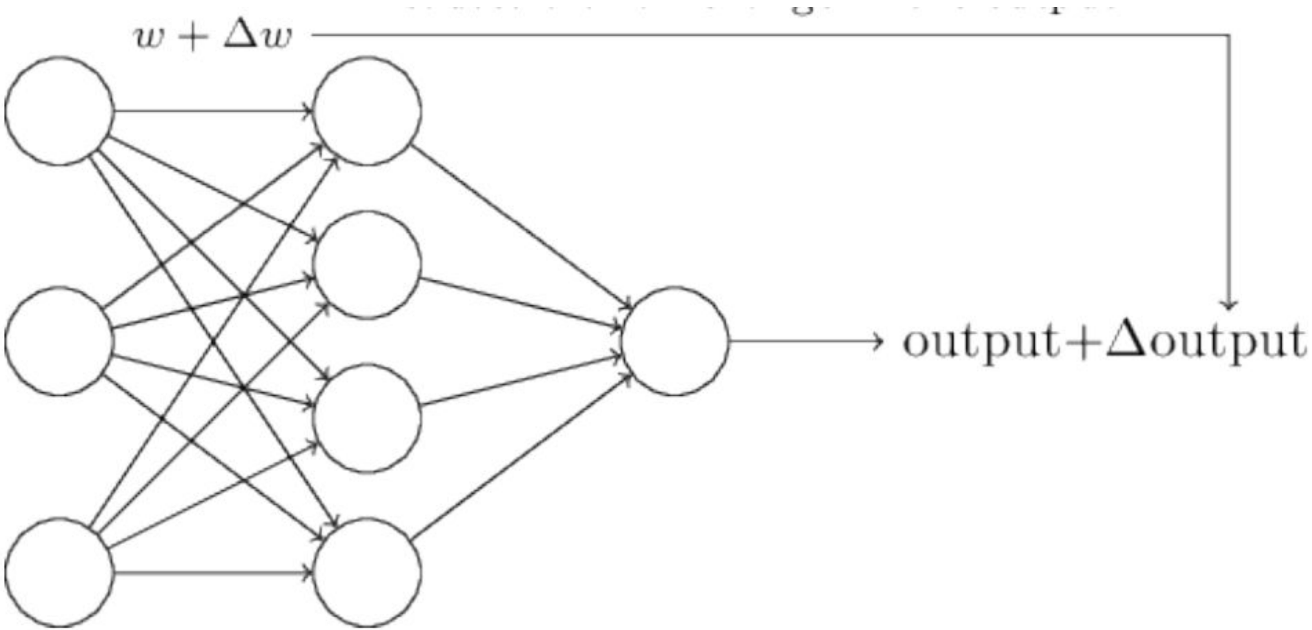
Neural Network





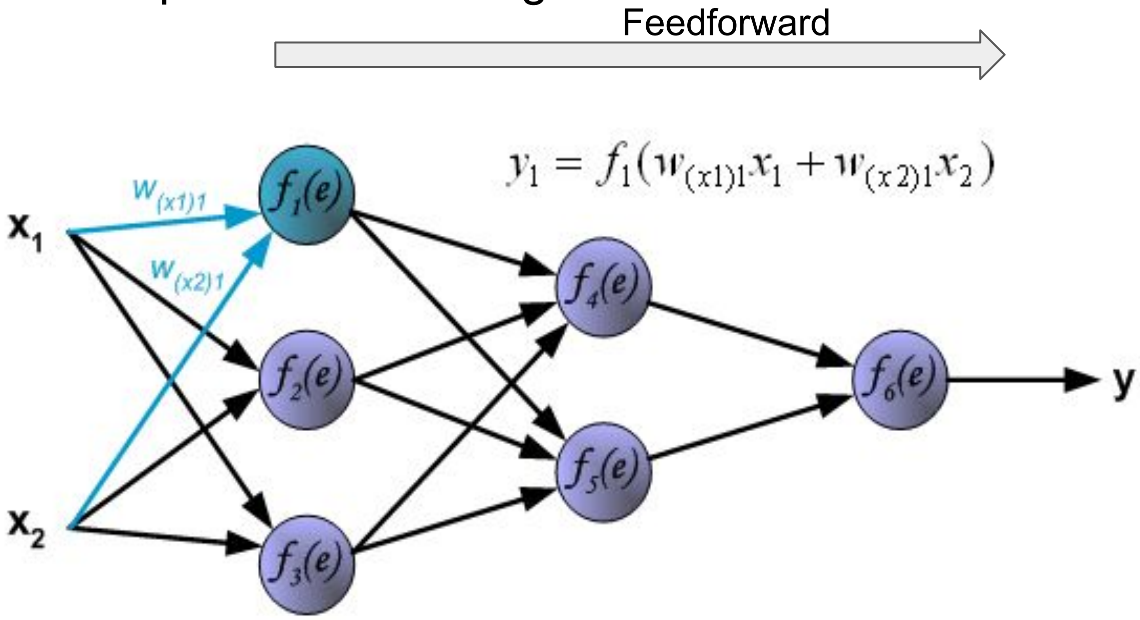
Neural Network

- Ouput changes as weight changes



Neural Network

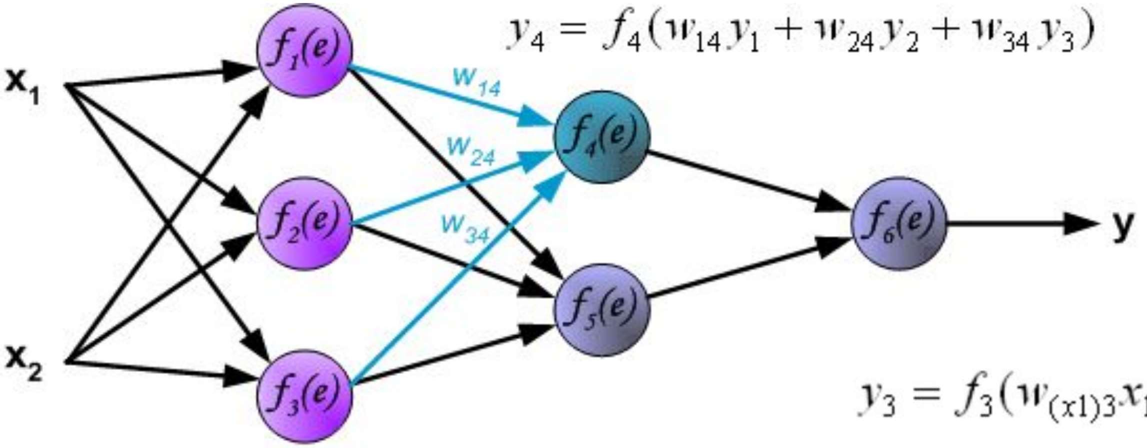
- Propagate the input forward through the network:



Neural Network

- Propagate the input forward through the network:

Feedforward



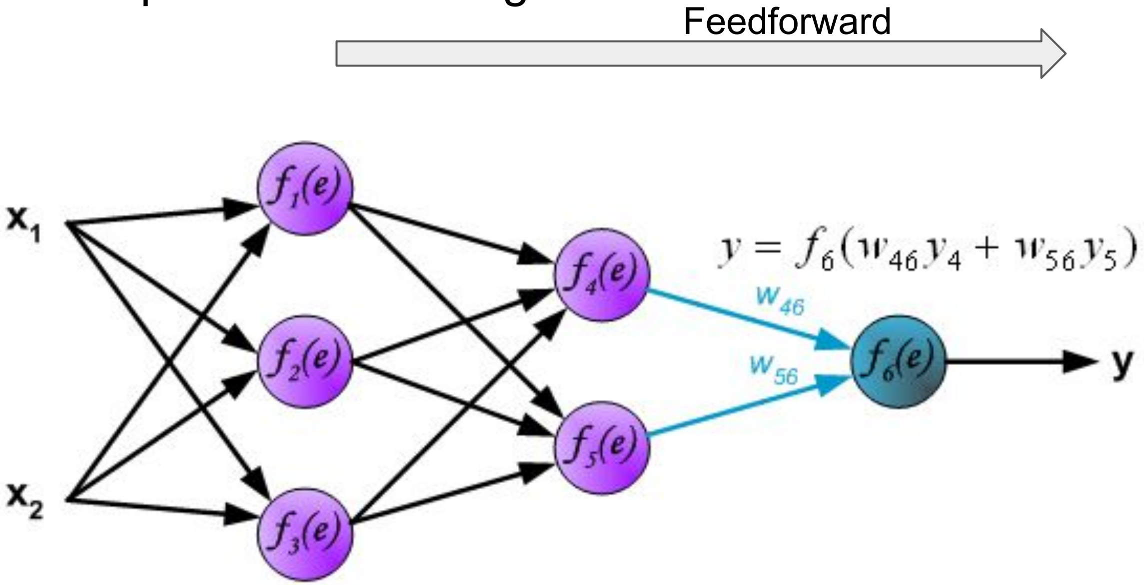
$$y_4 = f_4(w_{14}y_1 + w_{24}y_2 + w_{34}y_3)$$

$$y_3 = f_3(w_{(x1)3}x_1 + w_{(x2)3}x_2)$$

$$y_2 = f_2(w_{(x1)2}x_1 + w_{(x2)2}x_2)$$

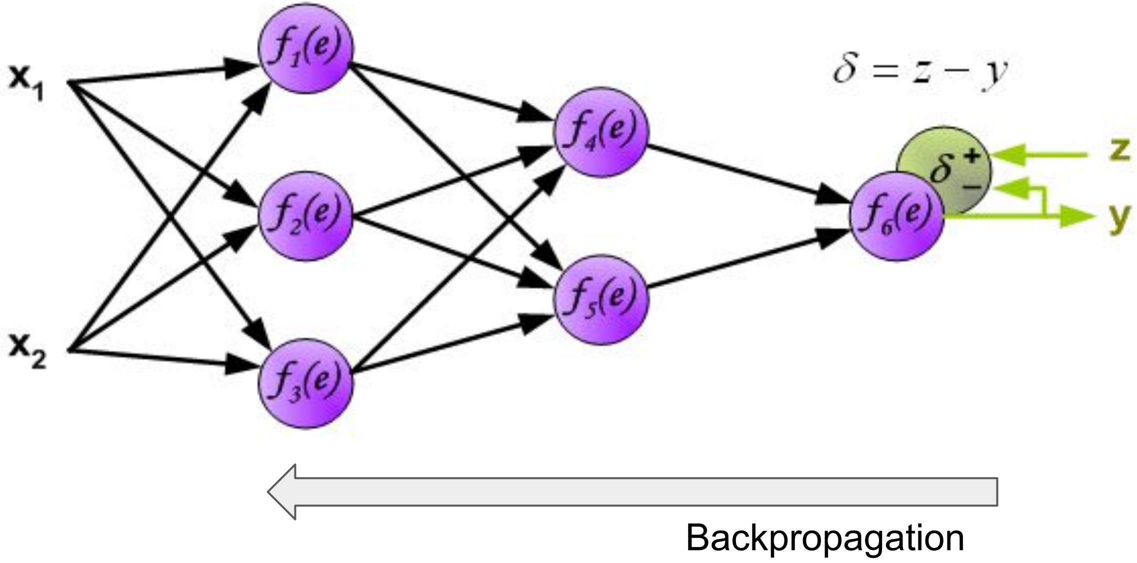
Neural Network

- Propagate the input forward through the network:



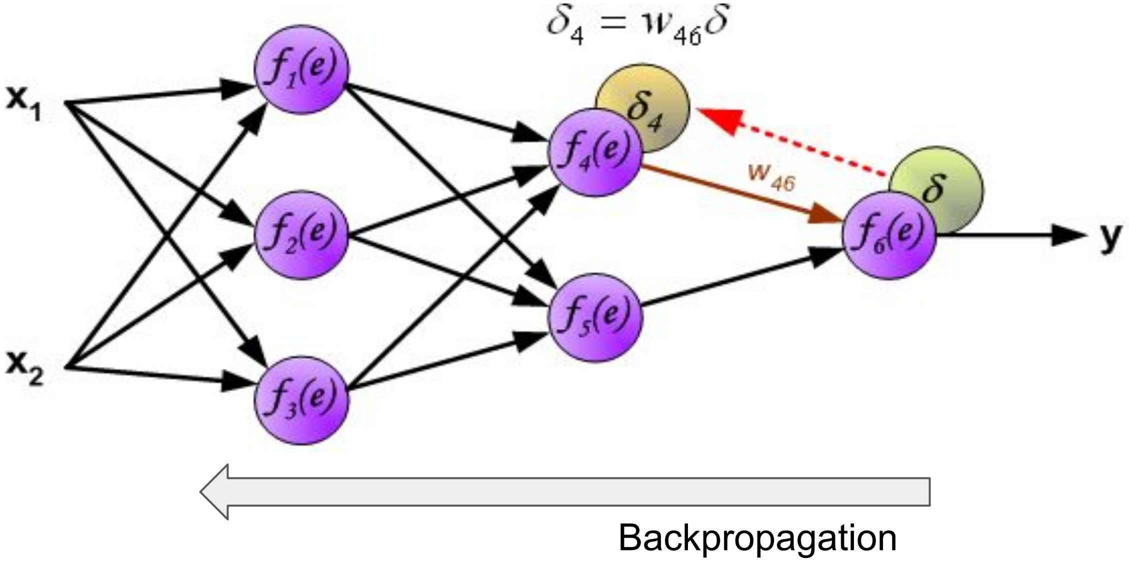
Neural Network

- Calculate the error



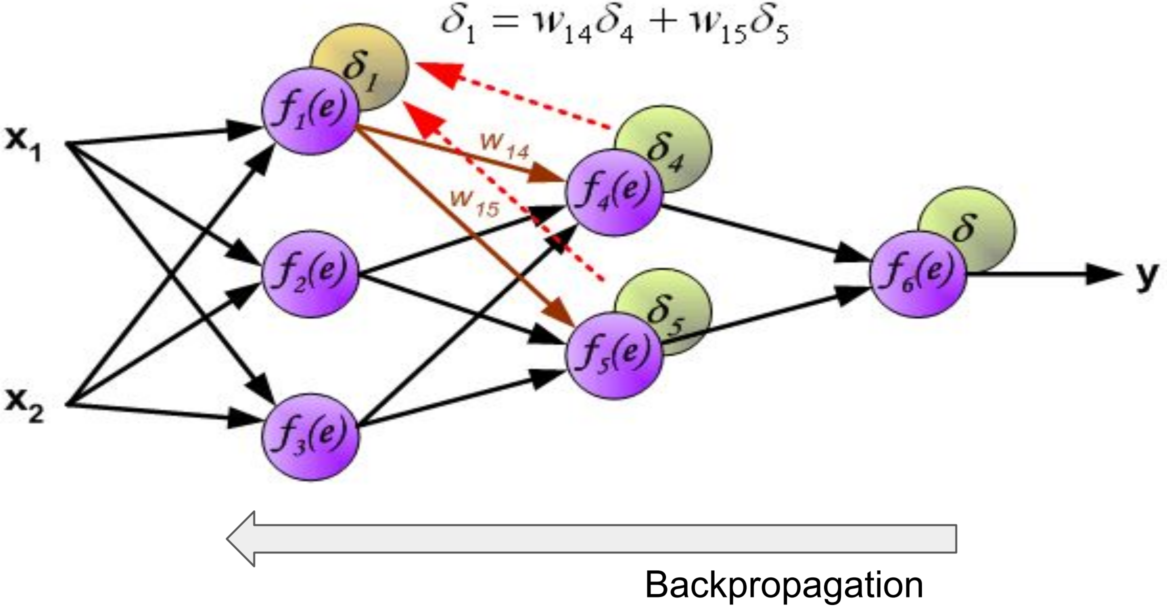
Neural Network

- Propagate the error backward through the network:

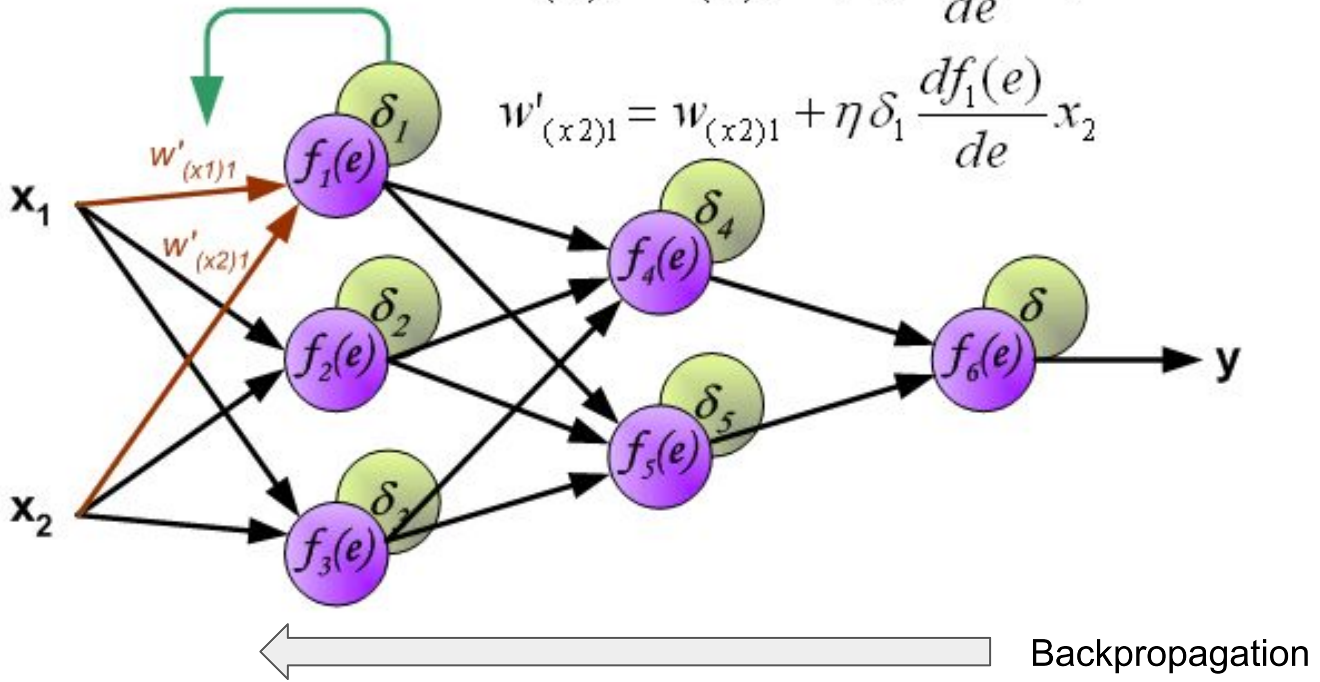


Neural Network

- Propagate the error backward through the network:



Neural Network



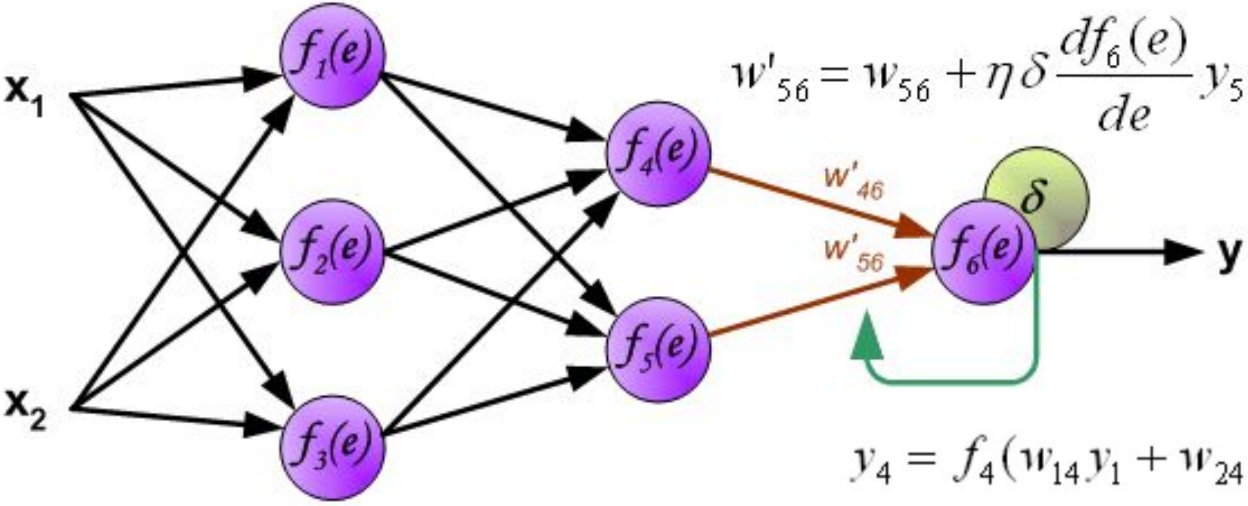
$$w'_{(x1)1} = w_{(x1)1} + \eta \delta_1 \frac{df_1(e)}{de} x_1$$

$$w'_{(x2)1} = w_{(x2)1} + \eta \delta_1 \frac{df_1(e)}{de} x_2$$

Neural Network

$$w'_{46} = w_{46} + \eta\,\delta\,\frac{df_6(e)}{de}\,y_4$$

$$w'_{56} = w_{56} + \eta\,\delta\,\frac{df_6(e)}{de}\,y_5$$

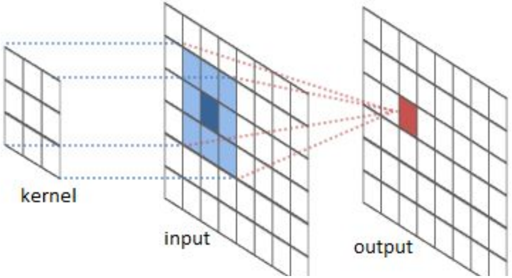


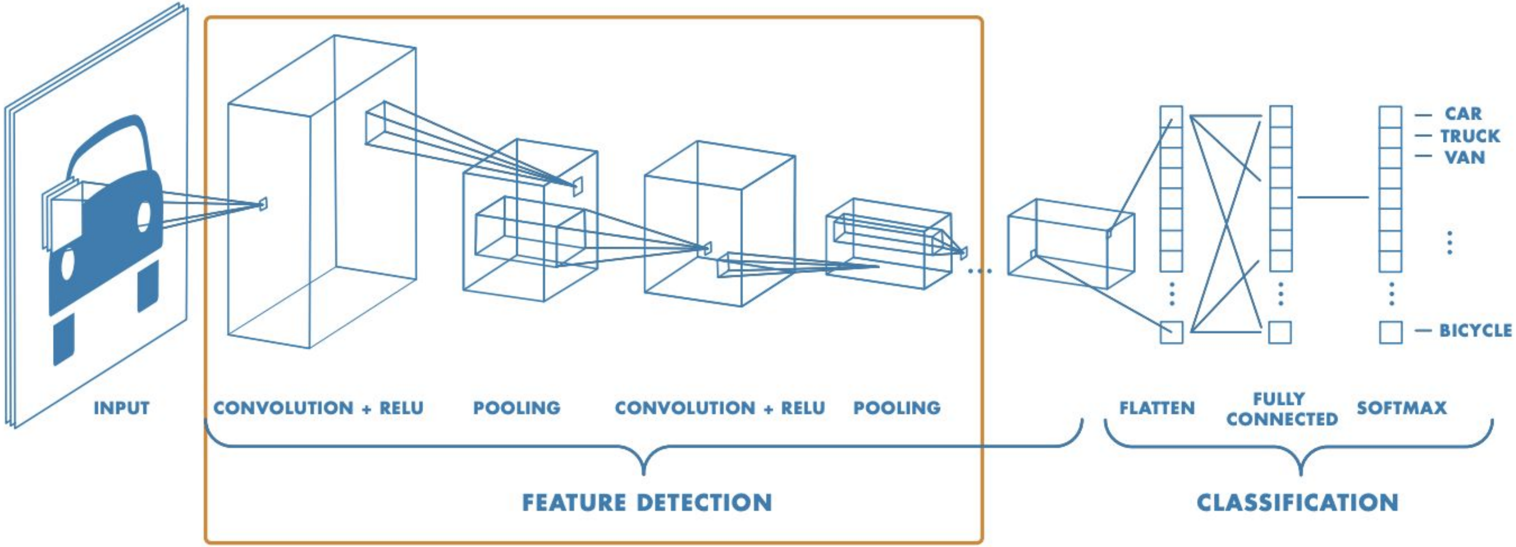
$$y_4 = f_4(w_{14}y_1 + w_{24}y_2 + w_{34}y_3)$$

$$y_5 = f_5(w_{15}y_1 + w_{25}y_2 + w_{35}y_3)$$

Convolutional Neural Network

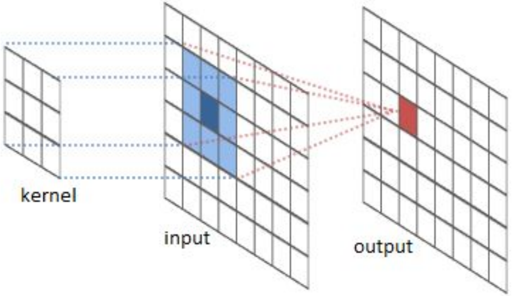
Convolution and Neural Network





Convolutional Neural Network

Convolution in image

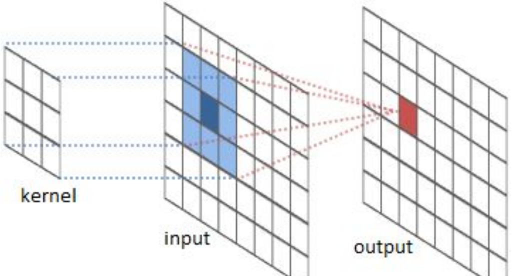


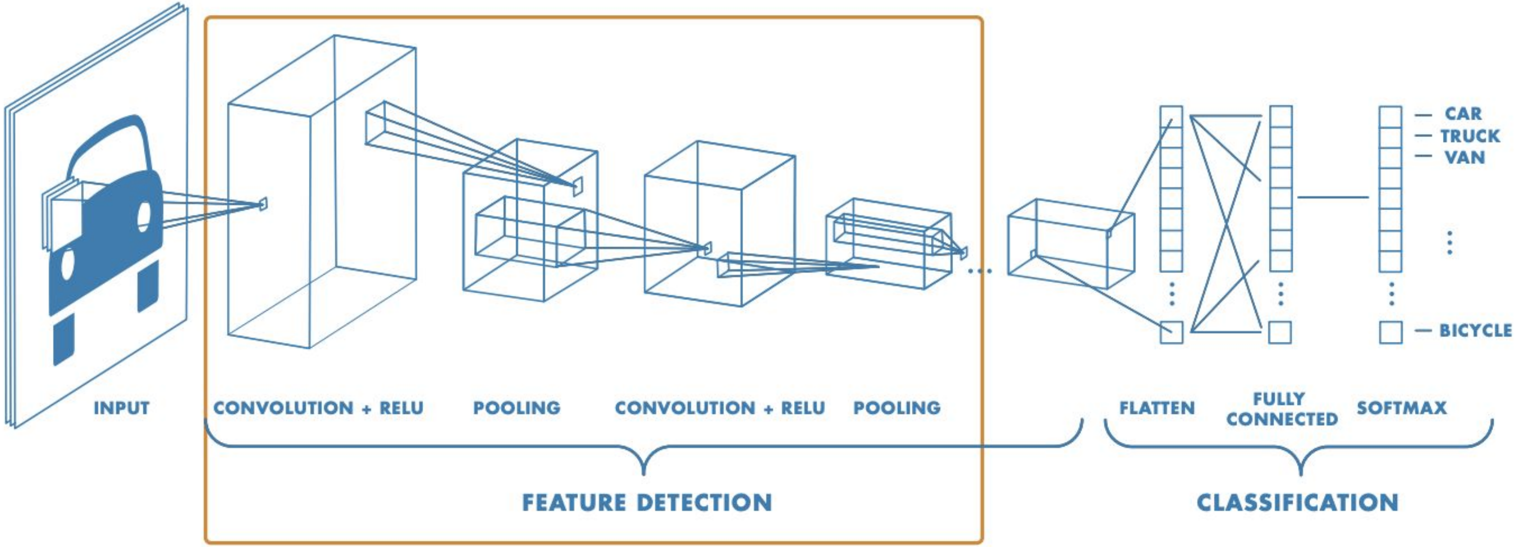
1	4	5	6
4	5	0	9
3	4	1	7
1	3	4	5

0	-1	0
-1	5	-1
0	-1	0

Convolutional Neural Network

Convolution and Neural Network





Machine Learning in Medical Imaging

- Mitosis Detection in Breast Cancer Histology Images via Deep Cascaded Networks
    - 12-layer CNN trained on samples from 50 2084 × 2084 RGB images manually annotated
    - 35 training images
    - 15 testing images

Mitosis Detection in Breast Cancer Histology Images via Deep Cascaded Networks
Hao Chen, Qi Dou, Xi Wang, Jing Qin, Pheng Ann Heng

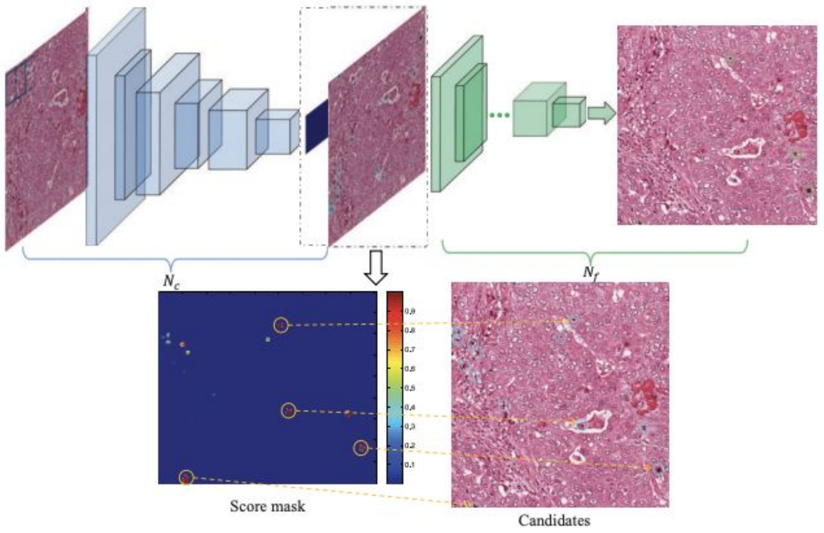
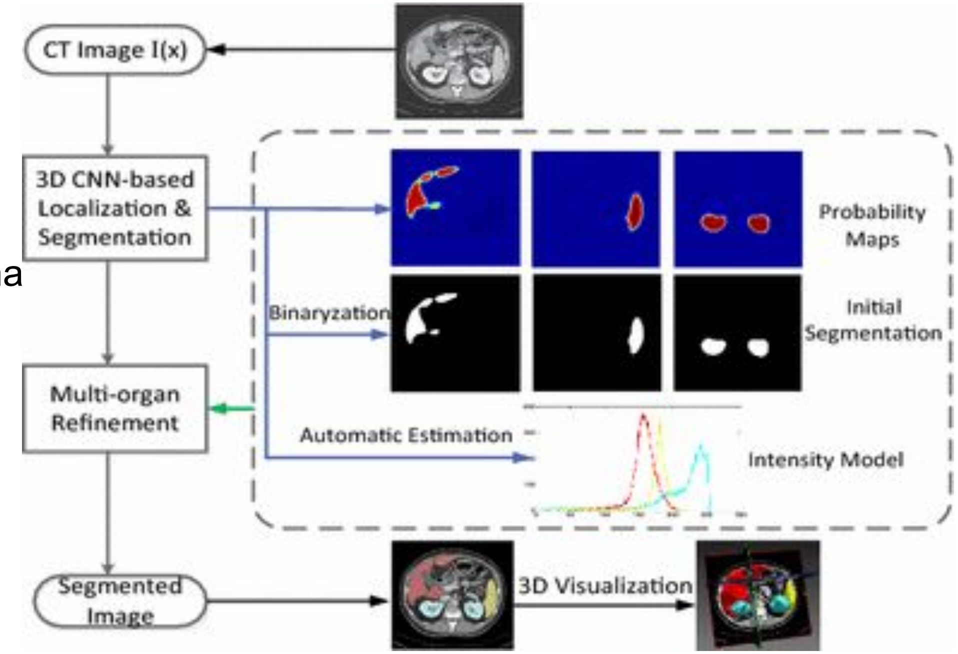


Figure 2: An overview of the proposed deep cascaded networks for fast and accurate mitosis detection.

Machine Learning in Medical Imaging

- Automatic abdominal multi-organ segmentation using deep convolutional neural network and time-implicit level sets
  - 10-layer CNN trained on 140 abdomina CT scans
  - 4 organ segmentation rate ≥ 94%
    - Liver
    - Spleen
    - Kidneys



Hu, Peijun, et al. "Automatic abdominal multi-organ segmentation using deep convolutional neural network and time-implicit level sets." International Journal of Computer Assisted Radiology and Surgery (2016): 1-13.

Machine Learning in Medical Imaging

- Colorectal Segmentation using Multiple Encoder-Decoder Network in Colonoscopy Images

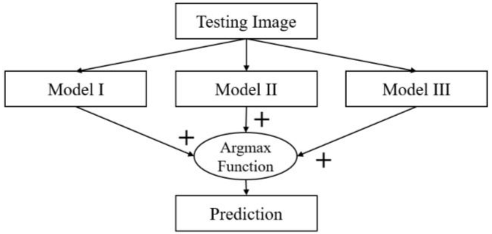


Fig. 3: Block diagram of the proposed model combination in testing phase.

Q. Nguyen and S. Lee, "Colorectal Segmentation Using Multiple Encoder-Decoder Network in Colonoscopy Images," *2018 IEEE First International Conference on Artificial Intelligence and Knowledge Engineering (AIKE)*, Laguna Hills, CA, 2018, pp. 208-211.

TABLE I: Result comparision with previous approaches.

Criterion	Accuracy	Dice score	mIoU	Database
[7]	0.975	0.701	NA	CVC-ClinicDB
[11]	0.977	0.810	NA	CVC-ClinicDB
[8]	0.949	NA	72.74	CVC-ClinicDB
Proposed Method	0.984	0.889	89.35	CVC-ClinicDB

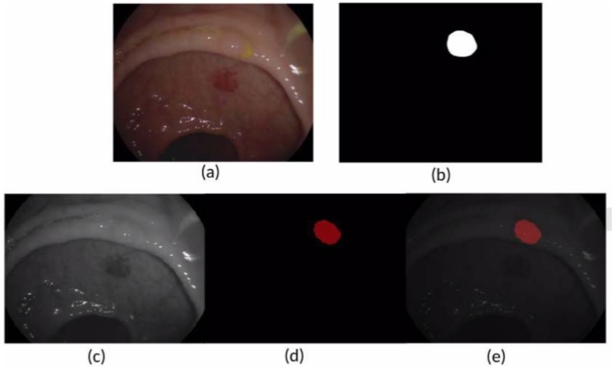


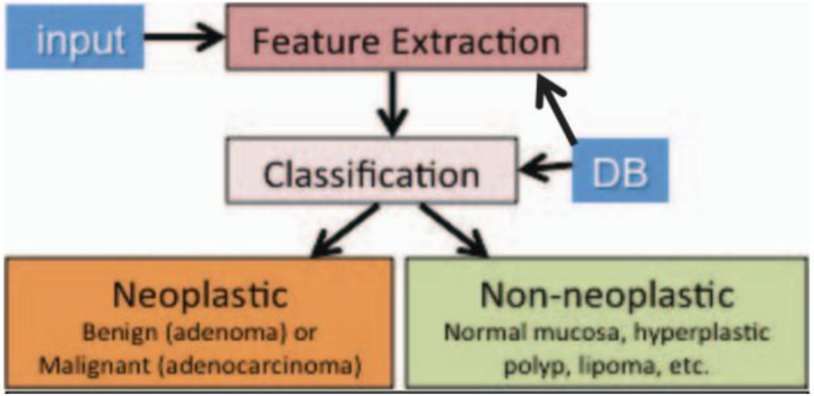
Fig. 4: Result in ETIS-LaribPolypDB testing set, (a) testing image, (b) response ground truth, (c) grayscale testing image, (d) prediction image, (e) prediction overlay image.

Polyps project

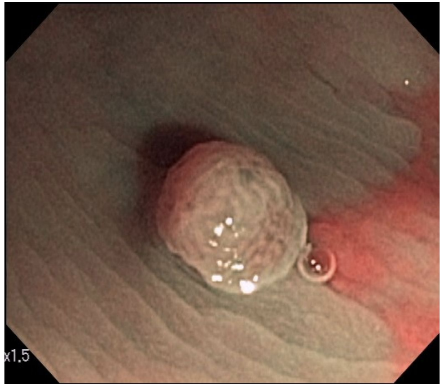
Narrow Band Imaging (NBI) vs. White Light (WL)

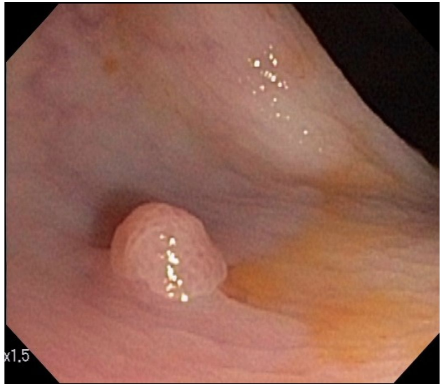
- 113 patients, 128 polyps
- 68 adenomas
- 60 non-adenomas

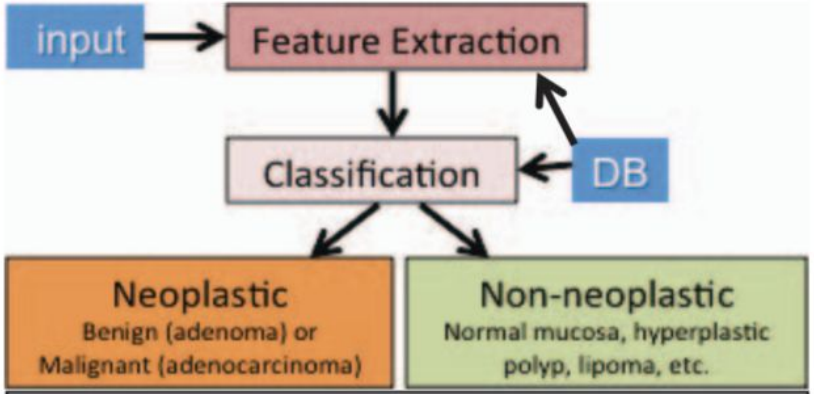
T. Dassopoulos, A. Karargyris, S. Makrogiannis and N. Bourbakis, "A preliminary study for automatic accurate detection of adenomatous polyps in the small intestine," *2017 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, Orlando, FL, 2017, pp. 117-120.

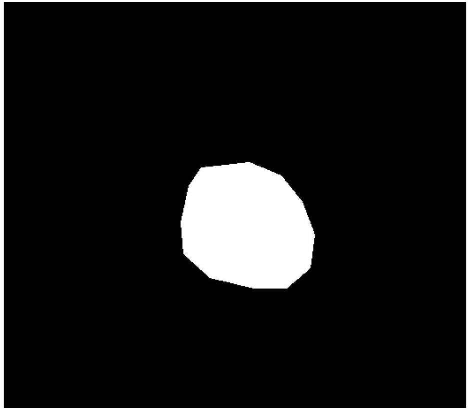


Polyps project



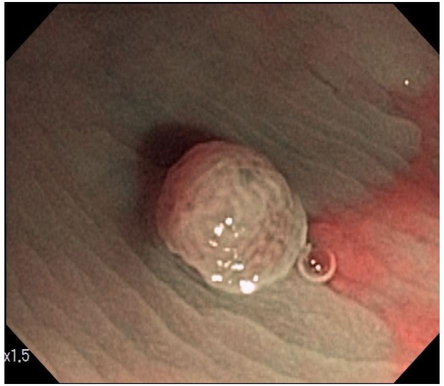


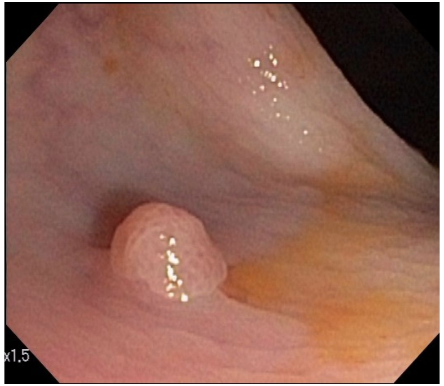


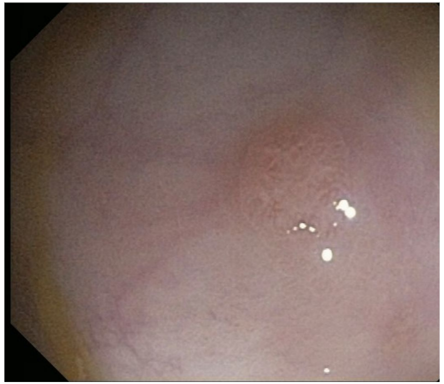


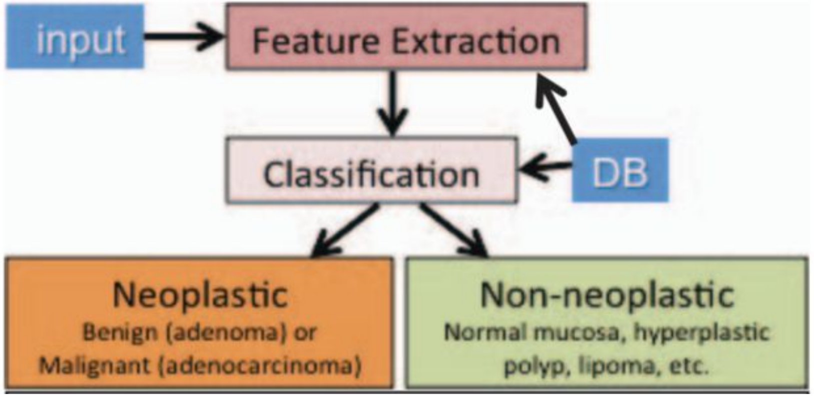
T. Dassopoulos, A. Karargyris, S. Makrogiannis and N. Bourbakis, "A preliminary study for automatic accurate detection of adenomatous polyps in the small intestine," *2017 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, Orlando, FL, 2017, pp. 117-120.

Polyps project









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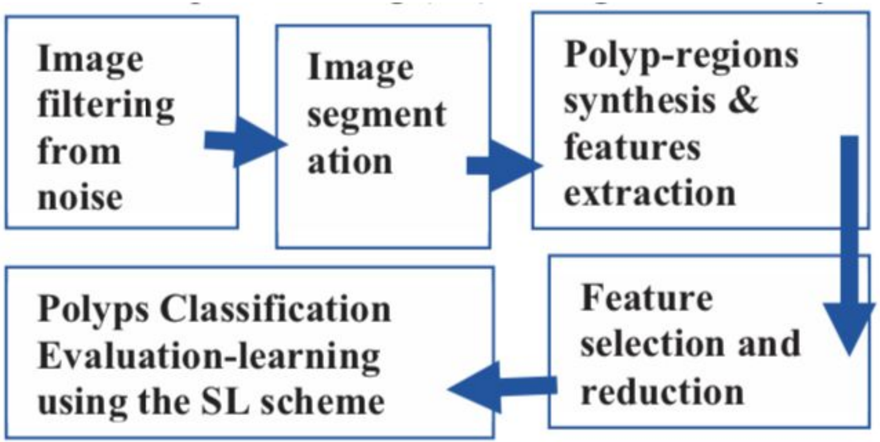
Polyps project

Features

- Color Layout Descriptor
- Edge Histogram Descriptor
- Color and Edge Directivity Descriptor
- Fuzzy Color and Texture Histogram Descriptor
- Gabor filter descriptor
- Gray Level Co- Occurrence Matrices (Haralick features)
- Tamura's texture features
- Edge Frequency descriptor
- Autocorrelation feature
- Primitive length feature.



Polyps project

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.706	0.483	0.623	0.706	0.662	0.664	Adenoma
	0.517	0.294	0.608	0.517	0.559	0.664	Non-Adenoma
Weighted Avg.	0.617	0.395	0.616	0.617	0.614	0.664	

Table 1. Classification Results for WL images set

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.794	0.433	0.675	0.794	0.73	0.769	Adenoma
	0.567	0.206	0.708	0.567	0.63	0.769	Non-Adenoma
Weighted Avg.	0.688	0.327	0.691	0.688	0.683	0.769	

Table 2. Classification Results for NBI images set

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.838	0.433	0.687	0.838	0.755	0.767	Adenoma
	0.567	0.162	0.756	0.567	0.648	0.767	Non-Adenoma
Weighted Avg.	0.711	0.306	0.719	0.711	0.705	0.767	

Table 3. Classification Results for both WL and NBI set

Goal:

archive ≥ 90% net percentage value of detection for adenoma

archive ≥ 90% agreement between the system-based and the standard, pathology-based recommendations

Polyps project