Unit -4

Deep Learning Medical Image Segmentation

21EC552

Prepared By: Dr. Anil B. Gavade

Element of Image Analysis

Preprocess
Image acquisition, restoration, and enhancement

↓

Intermediate process
Image segmentation and feature extraction

↓

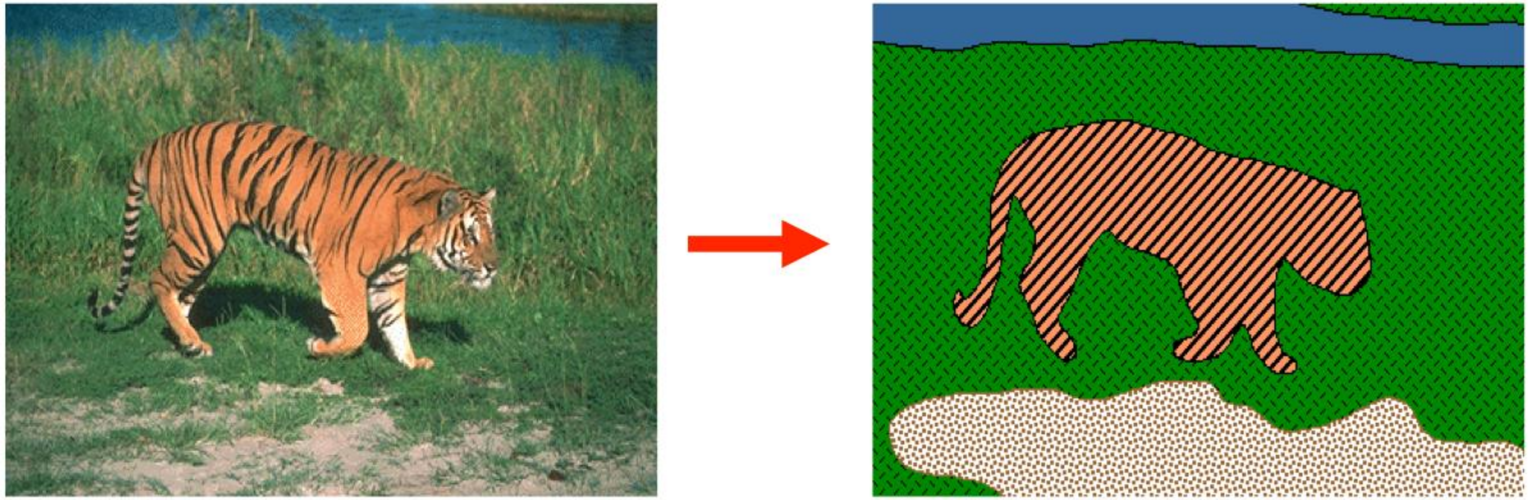
High level process
Image interpretation and recognition

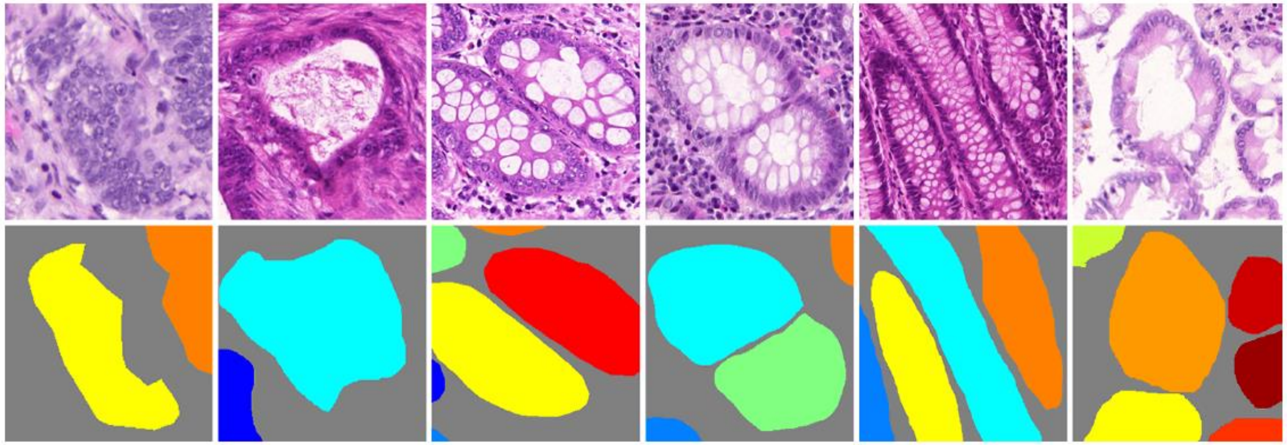
Digital image segmentation

Digital image segmentation in computer vision involves dividing an image into segments or regions based on specific criteria. This simplifies image representation, aiding analysis and information extraction. Segmentation is vital in computer vision for tasks like object recognition, image editing, medical imaging, and autonomous vehicles.

Image segmentation involves breaking down a digital image into various subgroups called image segments.

Digital image segmentation





Operators - Filters for Edge and Line Detection

Importance of Image Segmentation

Image segmentation is used to separate an image into constituent parts based on some image attributes. Image segmentation is an important step in image analysis

Benefit

1. Image segmentation reduces huge amount of unnecessary data while retaining only importance data for image analysis
2. Image segmentation converts bitmap data into better structured data which is easier to be interpreted

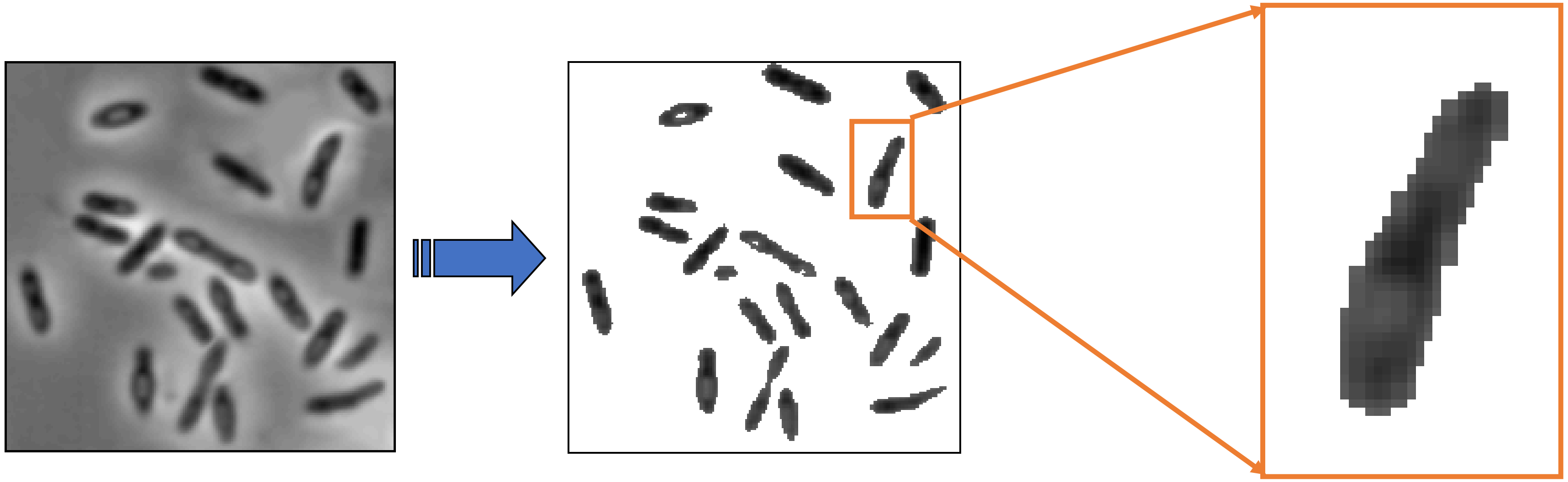
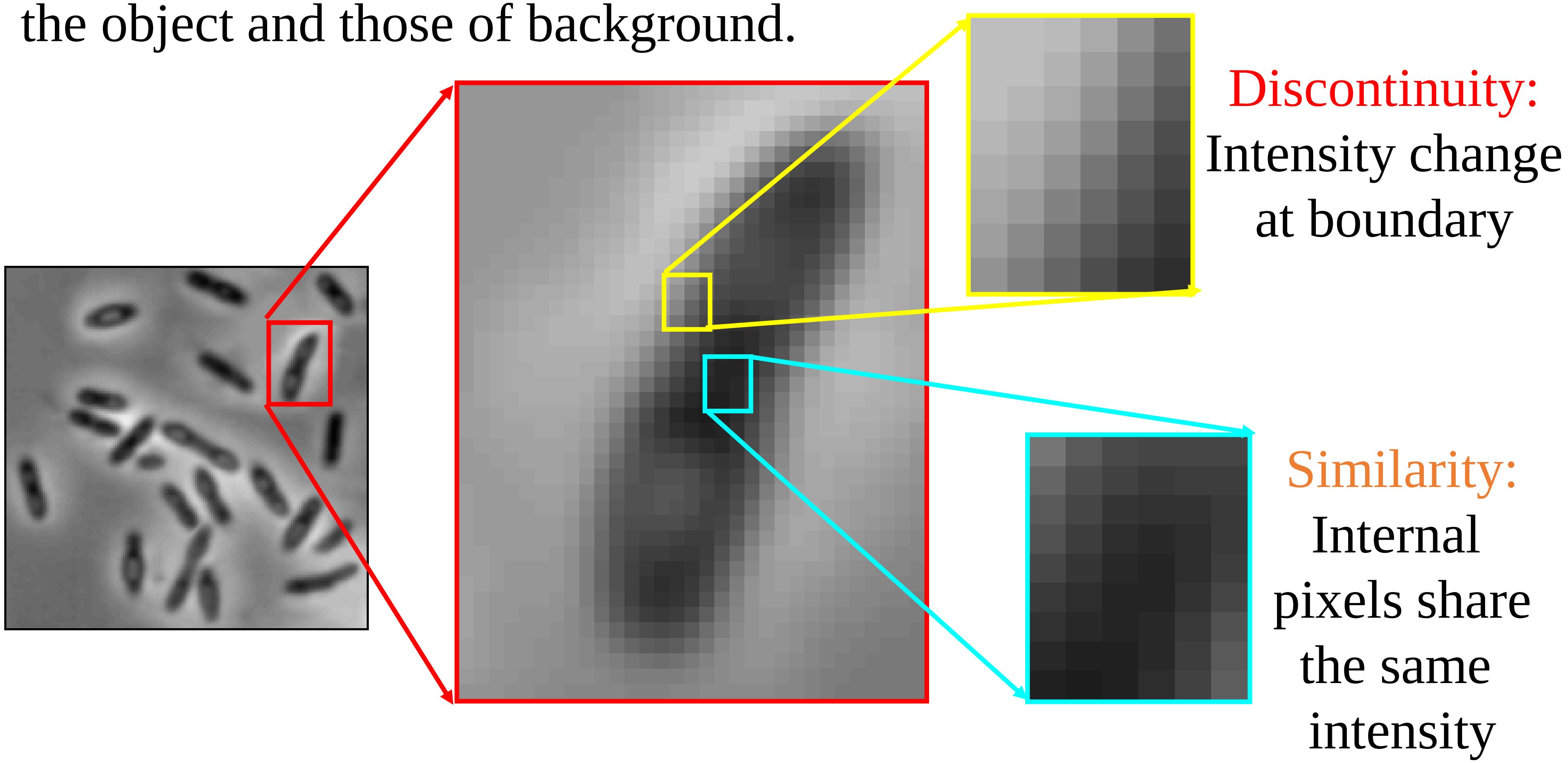


Image Attributes for Image Segmentation

1. Similarity properties of pixels inside the object are used to group pixels into the same set.

2. Discontinuity of pixel properties at the boundary between object and background is used to distinguish between pixels belonging to the object and those of background.



Spatial Filtering Application to Shape Detection

- ❖ One application of spatial filtering is shape detection: finding locations of objects with the desired shape.

- ❖ Unlike frequency selective masks that are designed based on the concept of frequency, shape detection masks are derived from the shapes to be detected themselves.

- ❖ A mask for shape detection usually contains the shape or a part of the shape to be detected.

- ❖ The location that is most correlated to the mask is the location where the highest filter response occurs. The shape is most likely to exist there.

Point Detection

❖ We can use Laplacian masks for point detection.

-1	-1	-1
-1	8	-1
-1	-1	-1

0	-1	0
-1	4	-1
0	-1	0

❖ Laplacian masks have the largest coefficient at the center of the mask while neighbor pixels have an opposite sign.

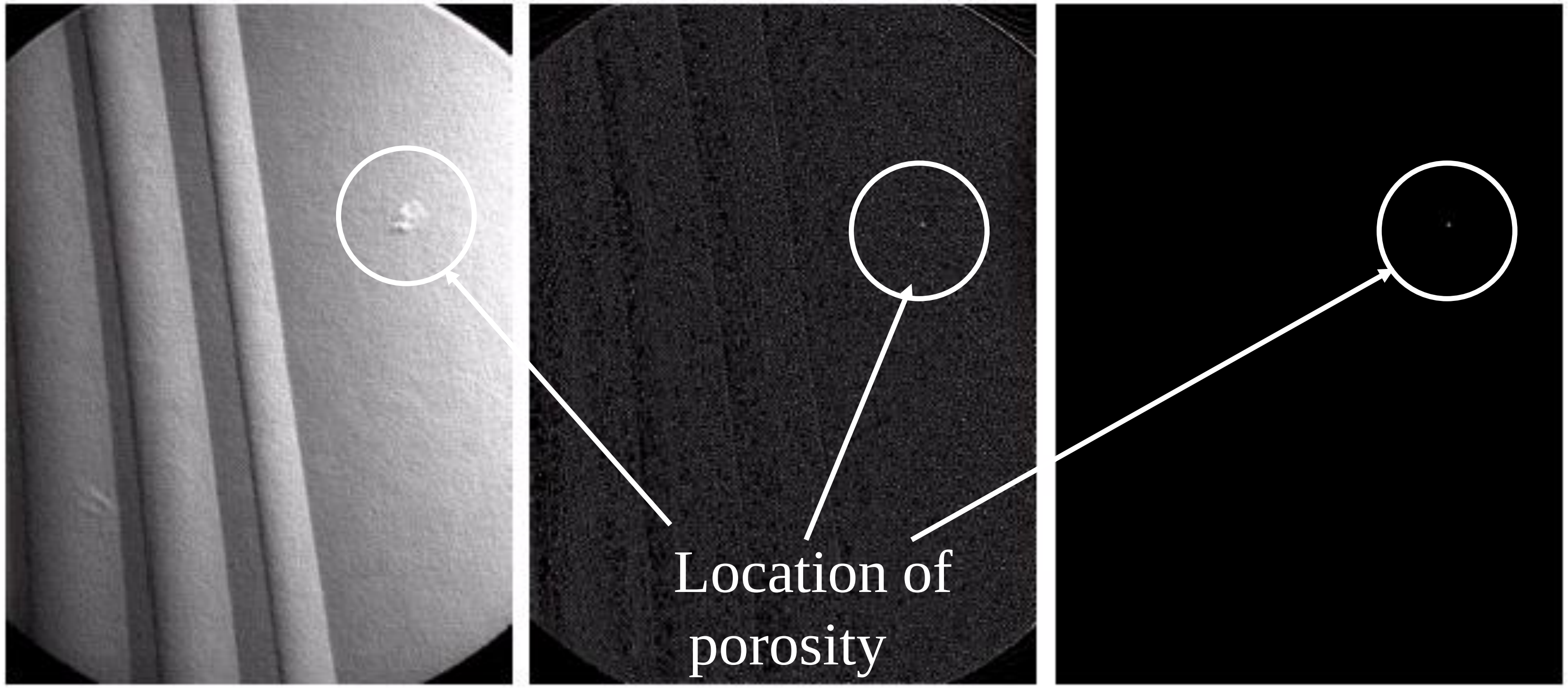
❖ This mask will give the high response to the object that has the similar shape as the mask such as isolated points.

❖ Notice that sum of all coefficients of the mask is equal to zero. This is due to the need that the response of the filter must be zero inside a constant intensity area

Point Detection

Point detection can be done by applying the thresholding function:

$$g(x,y) = \begin{cases} 1 & |\nabla f(x,y)| \geq T \\ 0 & \text{otherwise} \end{cases}$$



X-ray image of the turbine blade with porosity

Laplacian image

After thresholding

(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

Line Detection

❖ Similar to point detection, line detection can be performed using the mask the has the shape look similar to a part of a line

❖ There are several directions that the line in a digital image can be.

❖ For a simple line detection, 4 directions that are mostly used are Horizontal, +45 degree, vertical and –45 degree.

−1	−1	−1
2	2	2
−1	−1	−1

Horizontal

−1	−1	2
−1	2	−1
2	−1	−1

+45°

−1	2	−1
−1	2	−1
−1	2	−1

Vertical

2	−1	−1
−1	2	−1
−1	−1	2

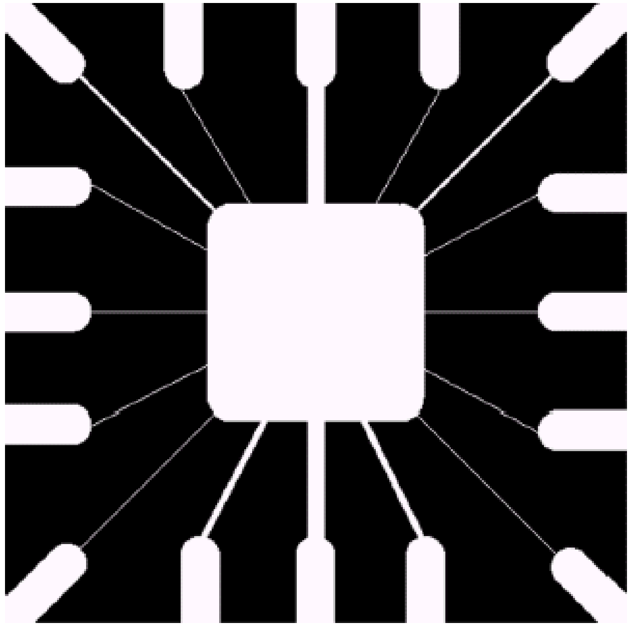
−45°

Line detection masks

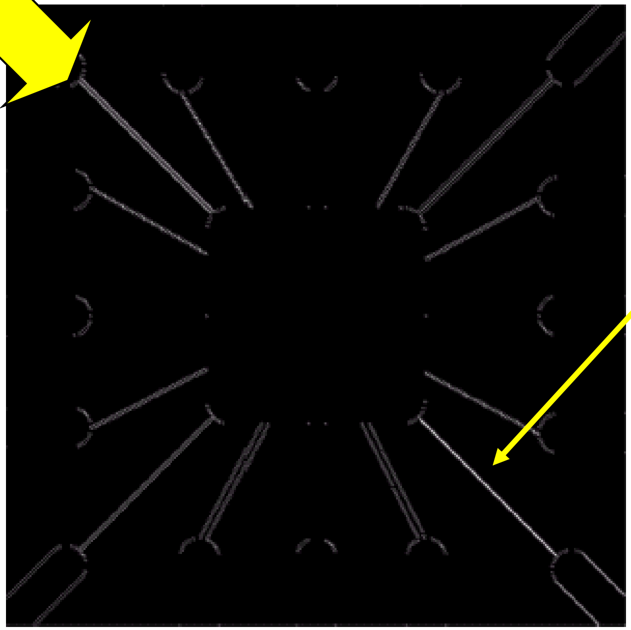
(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

Line Detection Example

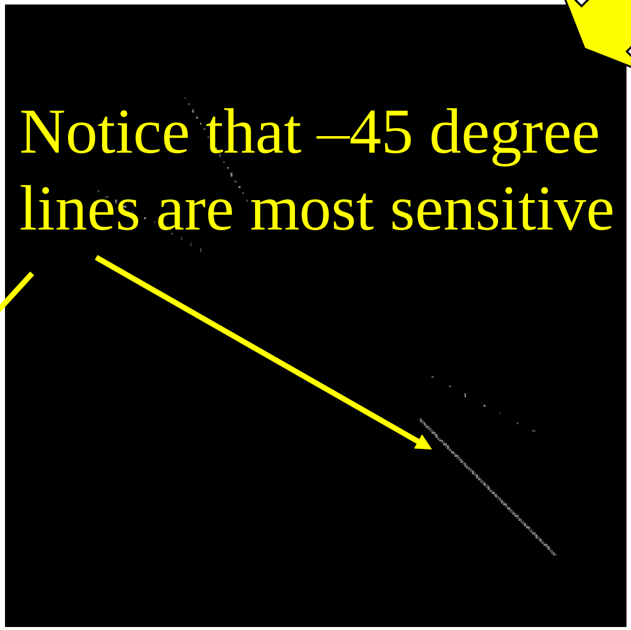
Binary wire bond mask image



Absolute value of result after processing with -45 line detector



Result after thresholding

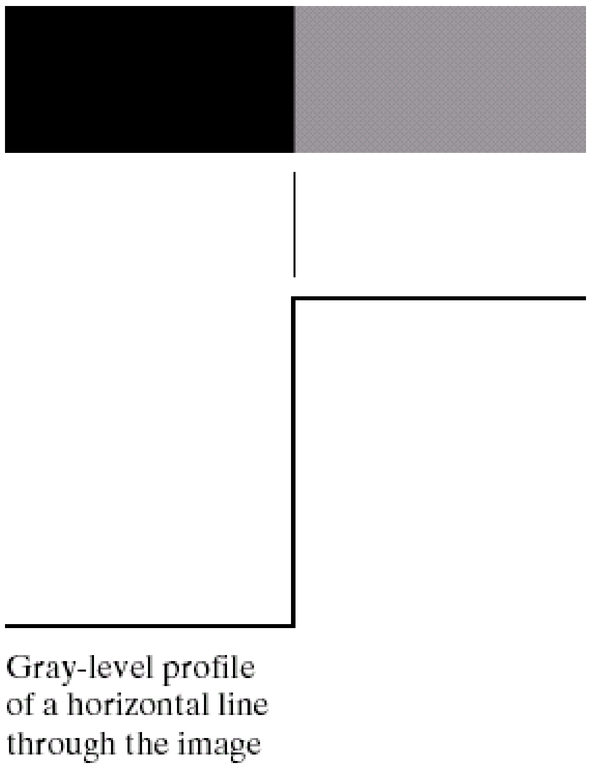


Notice that –45 degree lines are most sensitive

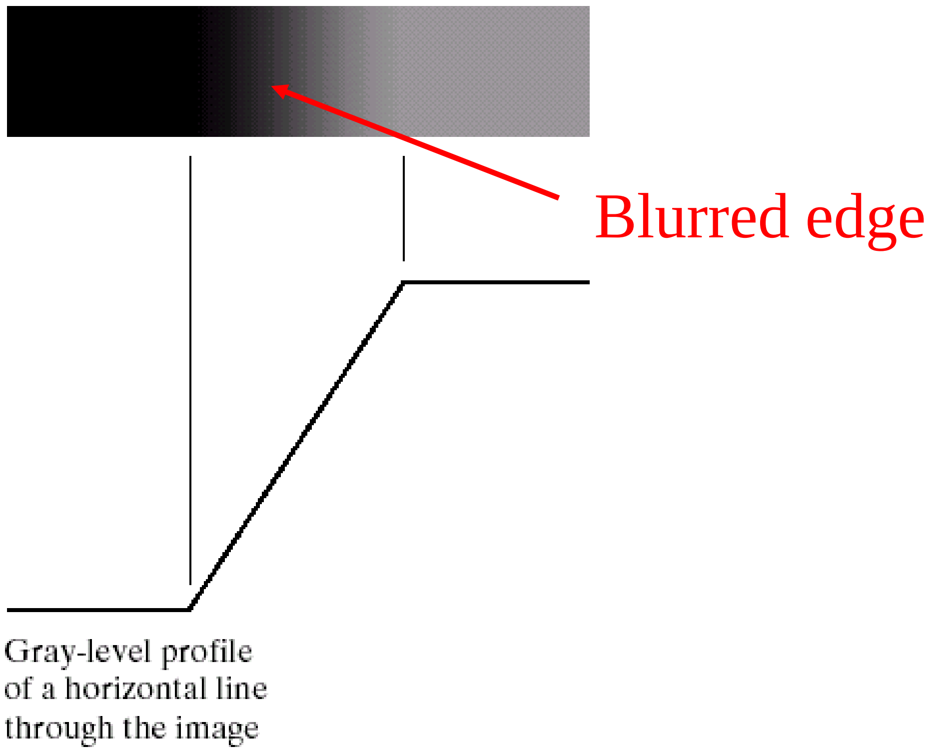
(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

Edges

Ideal step edge



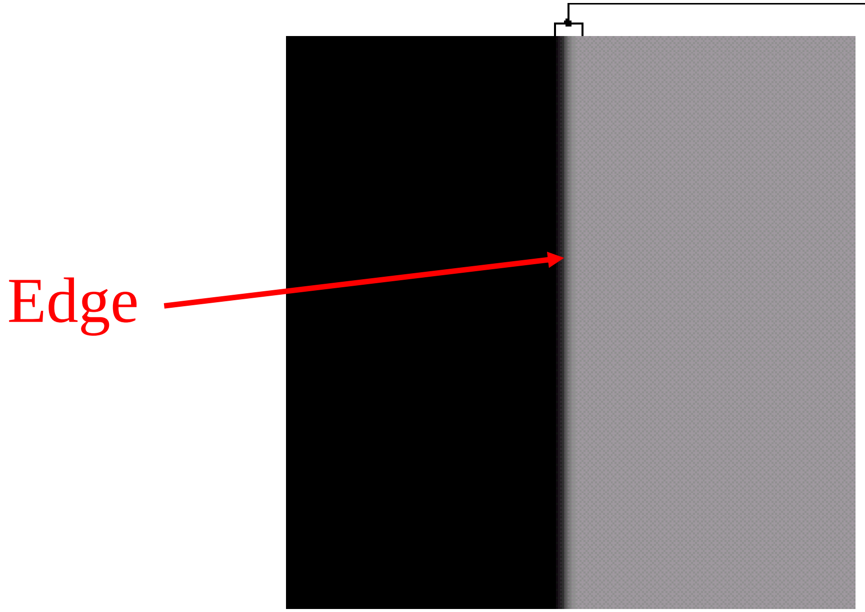
Ideal ramp edge



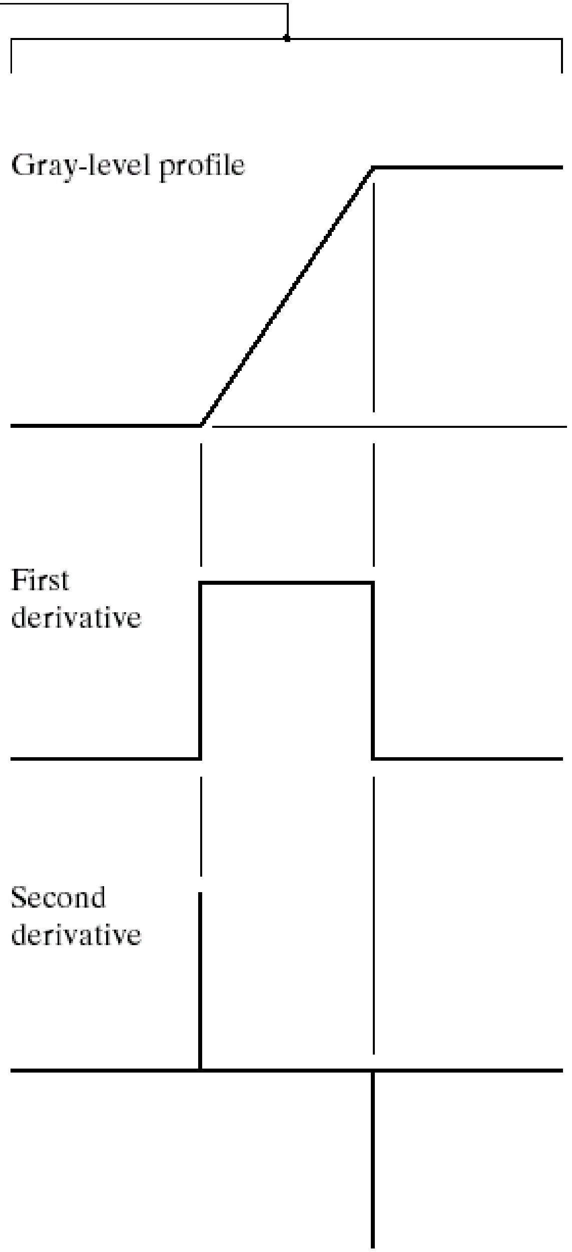
Generally, objects and background have different intensities. Therefore,
Edges of the objects are the areas where abrupt intensity changes occur.

(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

Ideal Ramp Edges and its Derivatives

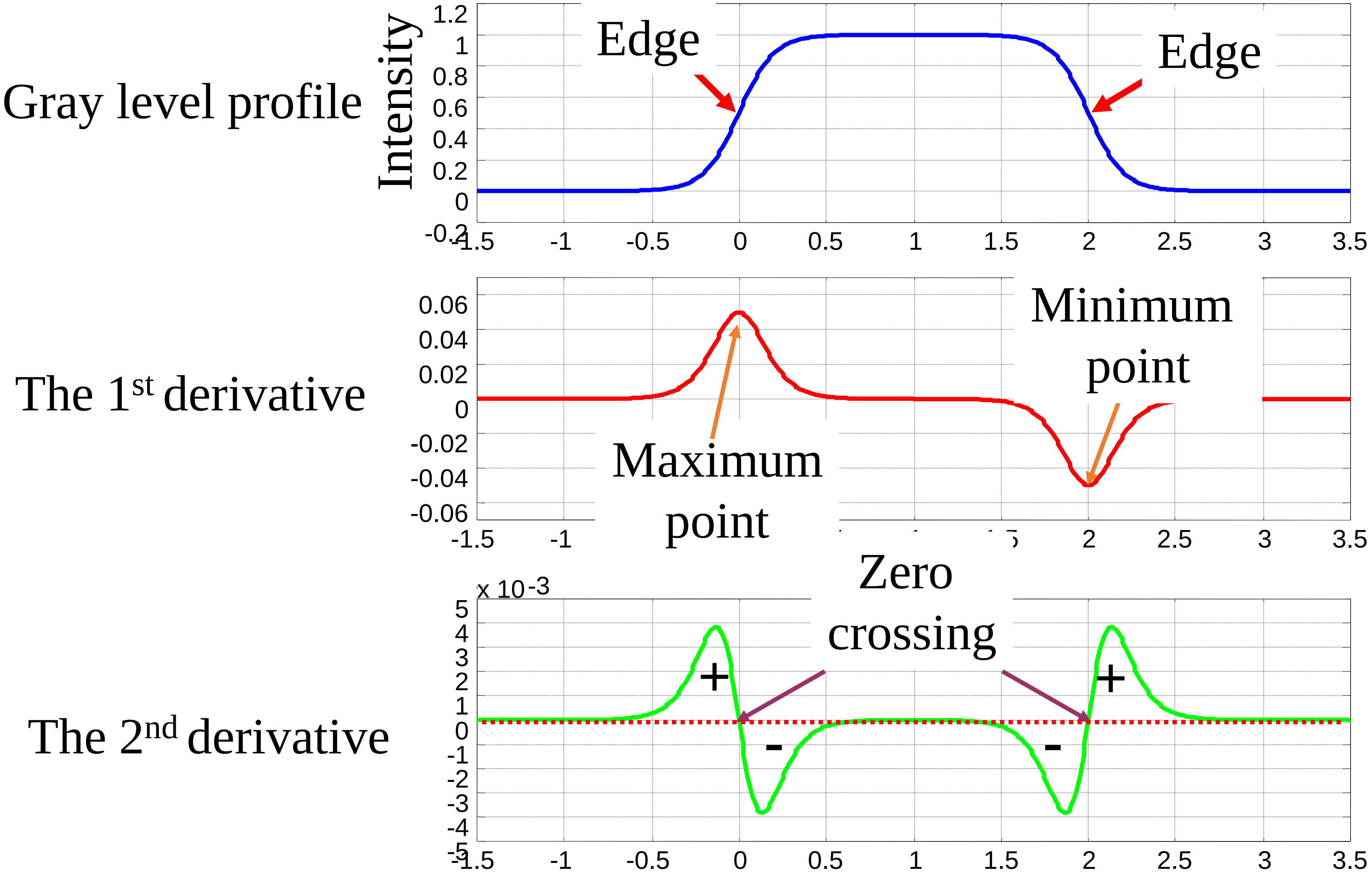


Original image



(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

Smoothed Step Edge and Its Derivatives



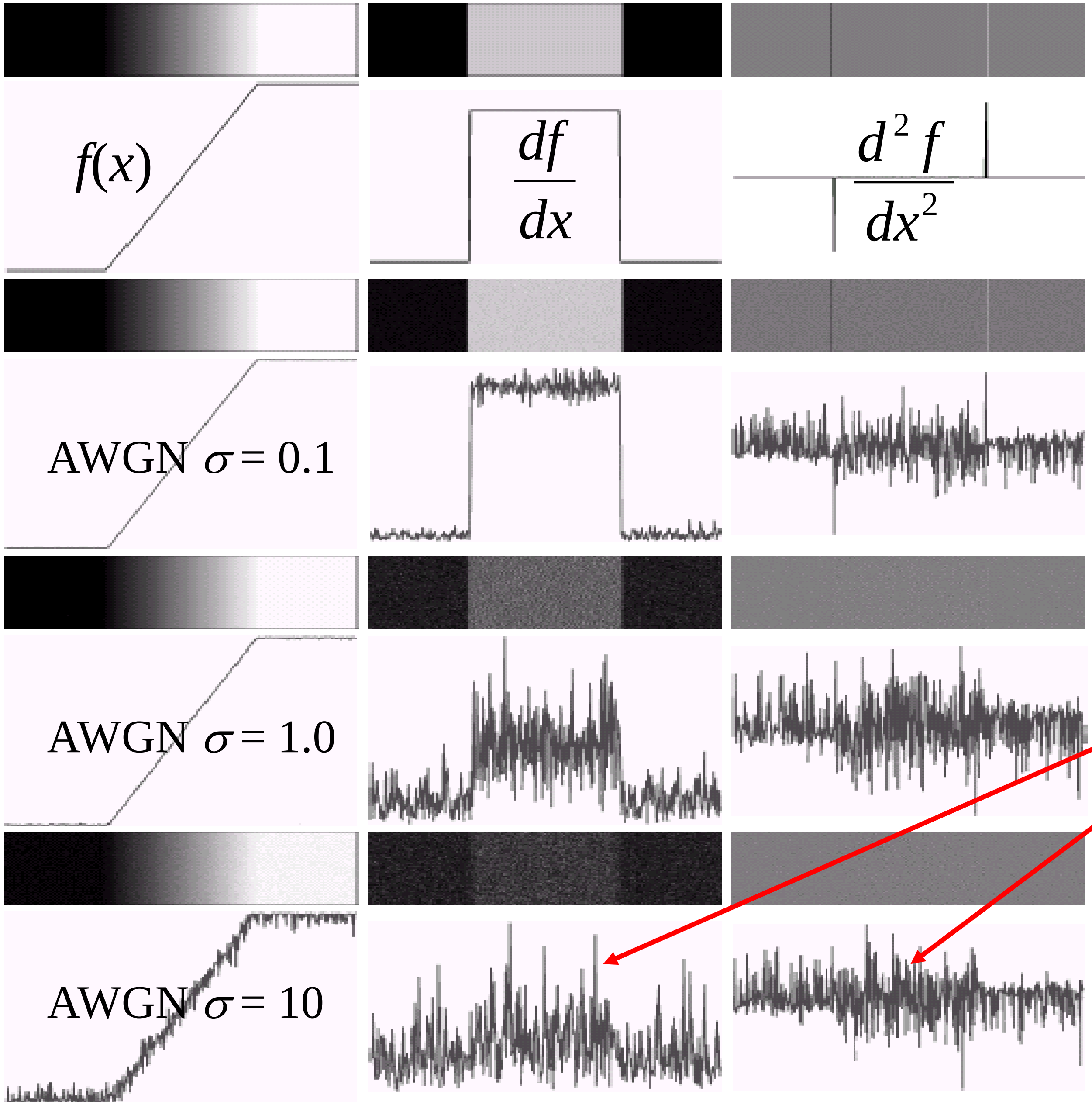
Derivative Based Edge Detection

❖ From the previous slide, we can conclude that:
Local maxima of the absolute of the 1^{st} derivative and Zero crossing of the 2^{nd} derivative occur at edges.

❖ Therefore, for detecting edges, we can apply zero crossing detection to the 2^{nd} derivative image or thresholding the absolute of the 1^{st} derivative image.

❖ Nevertheless, derivative operator is very sensitive to noise as we will see in the next slide.

Noisy Edges and Derivatives



Derivative operator is a highpass filter and thus enhances noise.

Edge responses are buried by noise.

(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

Masks for Estimating Partial Derivatives

Normally, the mask for estimating partial derivative is anti-symmetry with respect to the orthogonal axis

−1	0
0	1

0	−1
1	0

Roberts

−1	−1	−1
0	0	0
1	1	1

−1	0	1
−1	0	1
−1	0	1

Prewitt

−1	−2	−1
0	0	0
1	2	1

−1	0	1
−2	0	2
−1	0	1

Sobel

For example, the Sobel mask for computing $\frac{\partial f}{\partial x}$ is anti-symmetry with respect to the y-axis. It has the positive sign on the right side and negative sign on the left side.

Notice that sum of all coefficients is equal to zero to make sure that the response of a constant intensity area is zero.

(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

Masks for Detecting Diagonal Edges

0	1	1
−1	0	1
−1	−1	0

−1	−1	0
−1	0	1
0	1	1

Prewitt

0	1	2
−1	0	1
−2	−1	0

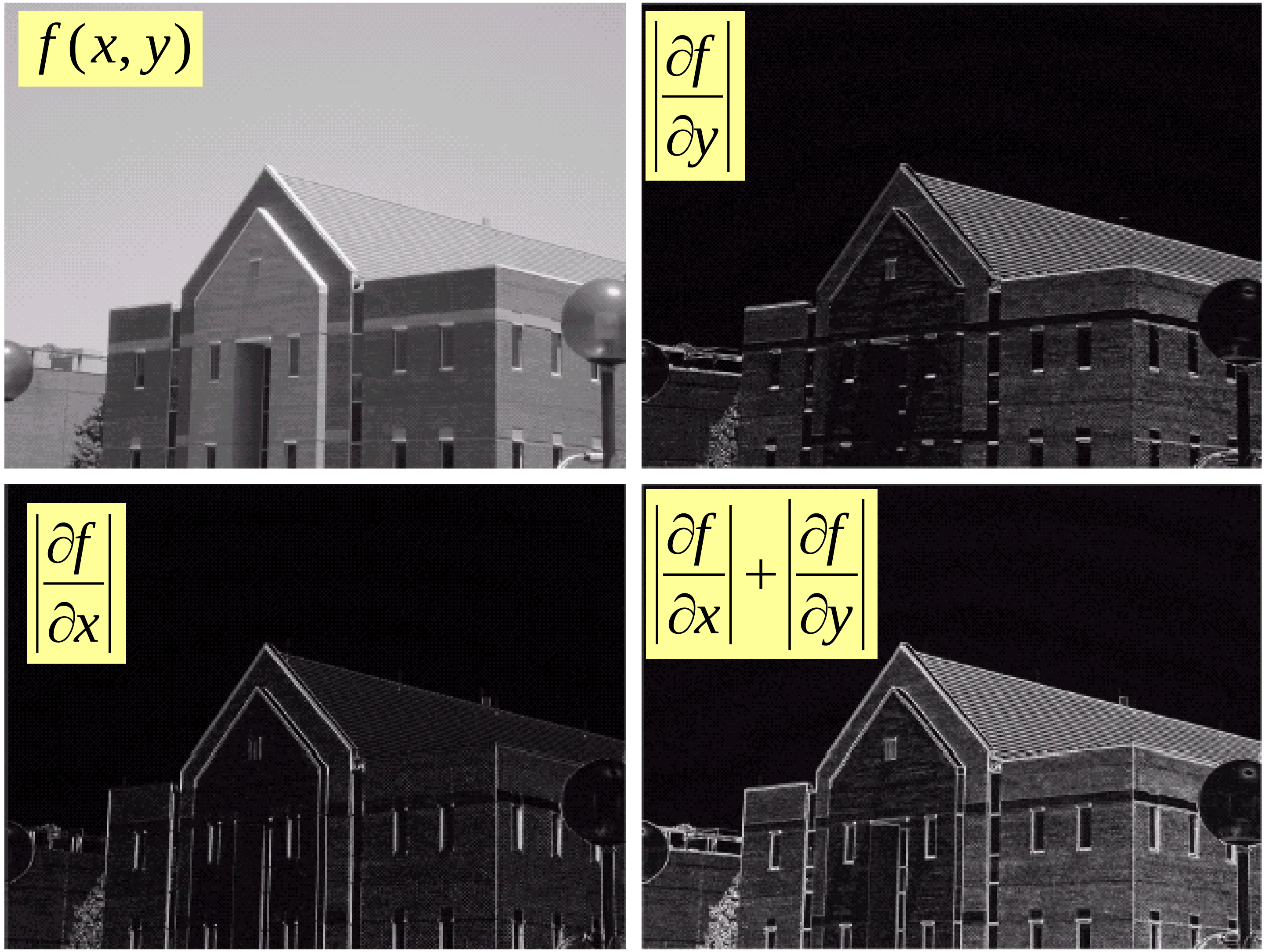
−2	−1	0
−1	0	1
0	1	2

Sobel

The mask for detecting -45-degree edges is anti-symmetry with respect to the –45-degree lines while the mask for detecting 45-degree edges is anti-symmetry with respect to the 45-degree lines.

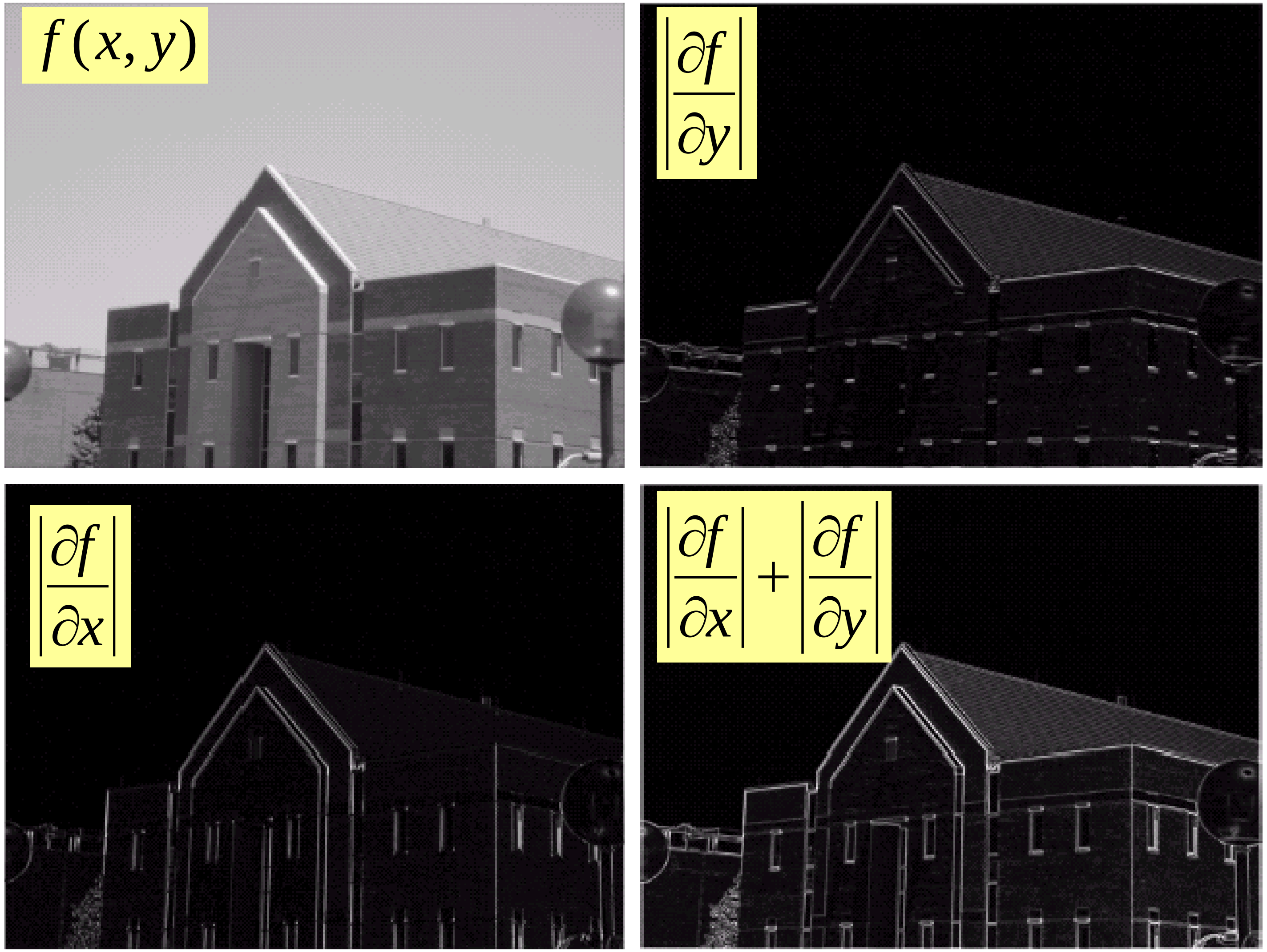
(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

Example of Image Gradient



(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

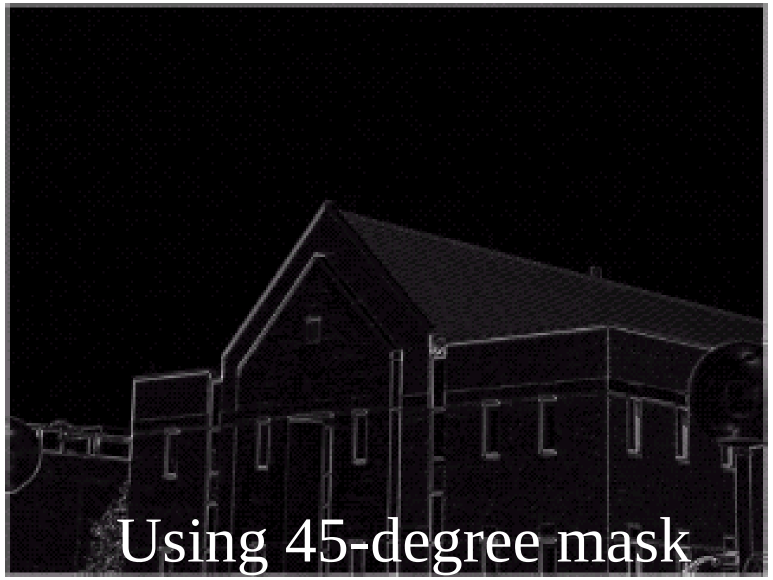
Example of Image Gradient



Note: the original image is smoothed by a 5x5 moving average mask first.

(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

Example of Diagonal Edges



0	1	2
−1	0	1
−2	−1	0

−2	−1	0
−1	0	1
0	1	2

Sobel

Note: the original image is smoothed by a 5x5 moving average mask first.

(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

Laplacian Masks

The Laplacian masks are used to estimate the Laplacian image:

$$\nabla^2 P = \frac{\partial^2 P}{\partial x^2} + \frac{\partial^2 P}{\partial y^2}$$

Ideally, the Laplacian mask must be directional invariant: symmetry in all direction (radially symmetry). However, for 3x3 masks, there are Only 8 possible directions. Hence, we can use the following masks:

0	−1	0
−1	4	−1
0	−1	0

−1	−1	−1
−1	8	−1
−1	−1	−1

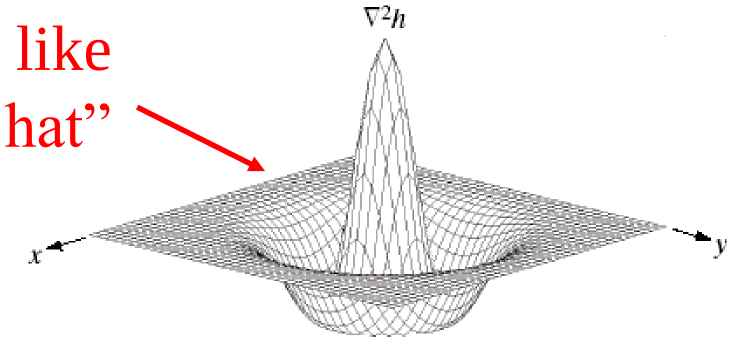
(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

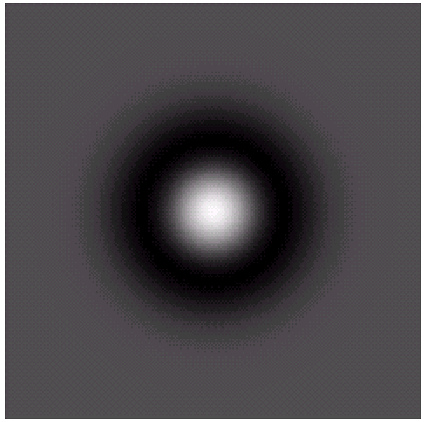
Laplacian Masks

For a large scale Laplacian mask, we can use a Laplacian of Gaussian (LOG) as a mask:

$$\nabla^2 G(x,y) = -\left[\frac{x^2+y^2-\sigma^2}{\sigma^4}\right] e^{-\left(\frac{x^2+y^2}{2\sigma^2}\right)}$$

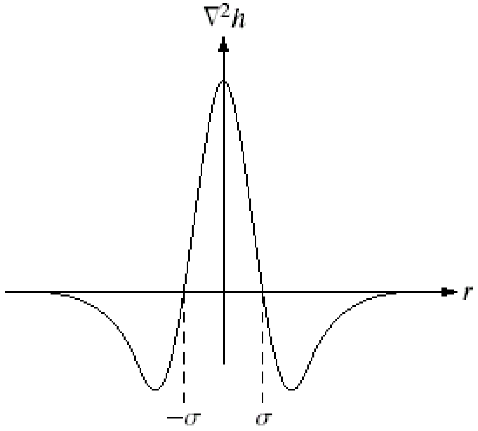
Surface plot of LOG, Looks like a "Mexican hat"





LOG image

Cross section of LOG



0	0	−1	0	0
0	−1	−2	−1	0
−1	−2	16	−2	−1
0	−1	−2	−1	0
0	0	−1	0	0

5x5 LOG mask

(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

Example of Laplacian Image

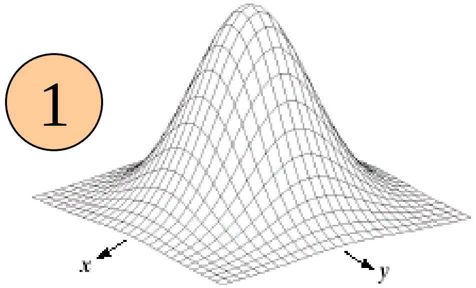
The angiogram image
(blood vessels)

$|\nabla P|$

We can compute the
Laplacian image by:

1. Smooth the image
by the Gaussian mask
2. Compute the Laplacian
image using the mask

1

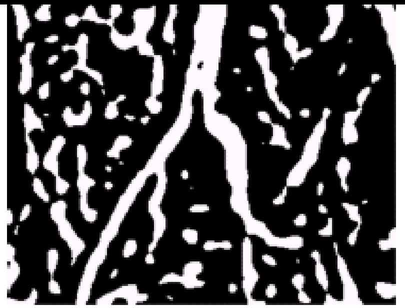


−1	−1	−1
−1	8	−1
−1	−1	−1

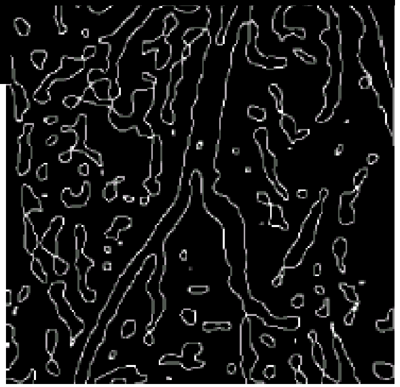
2

$\nabla^2 G * P$

Threshold of
The left image



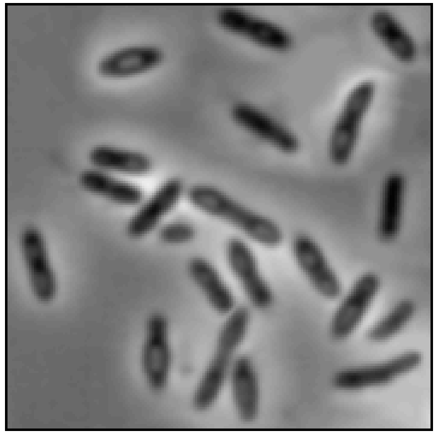
Zero crossing



(Images from Rafael C. Gonzalez and Richard E.
Wood, Digital Image Processing, 2nd Edition.

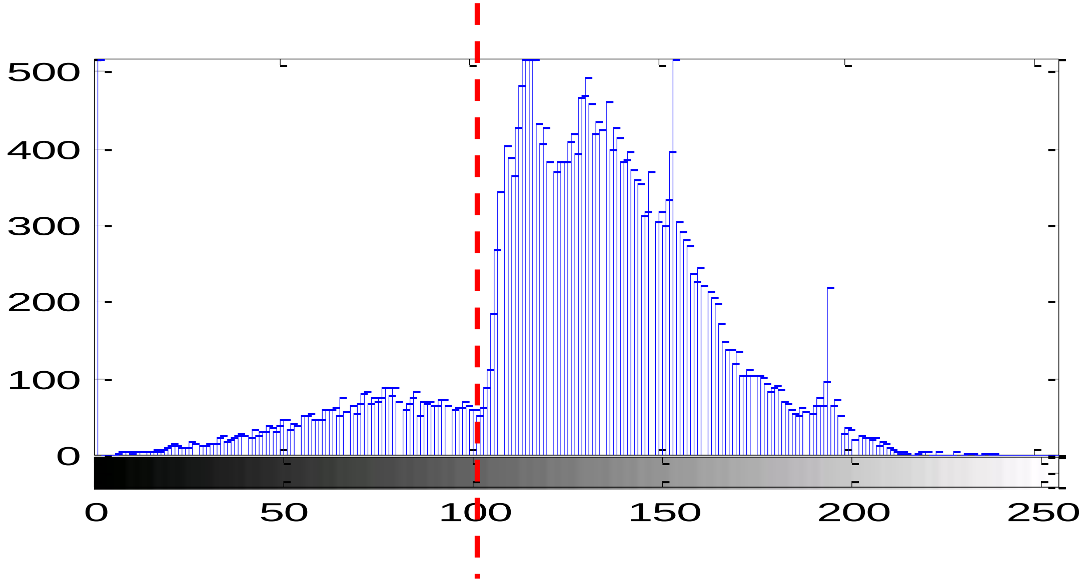
Pixel Oriented Image Segmentation: Thresholding

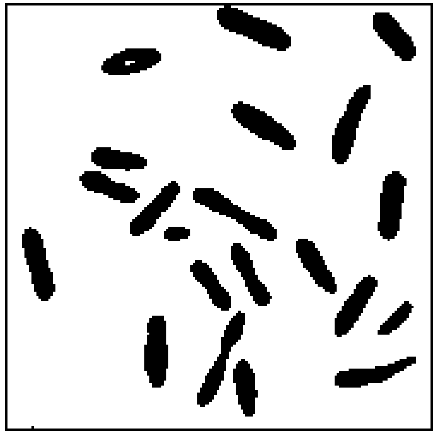
Intensity Thresholding



$$g(x,y) = \begin{cases} 1 & f(x,y) > T \\ 0 & f(x,y) < T \end{cases}$$

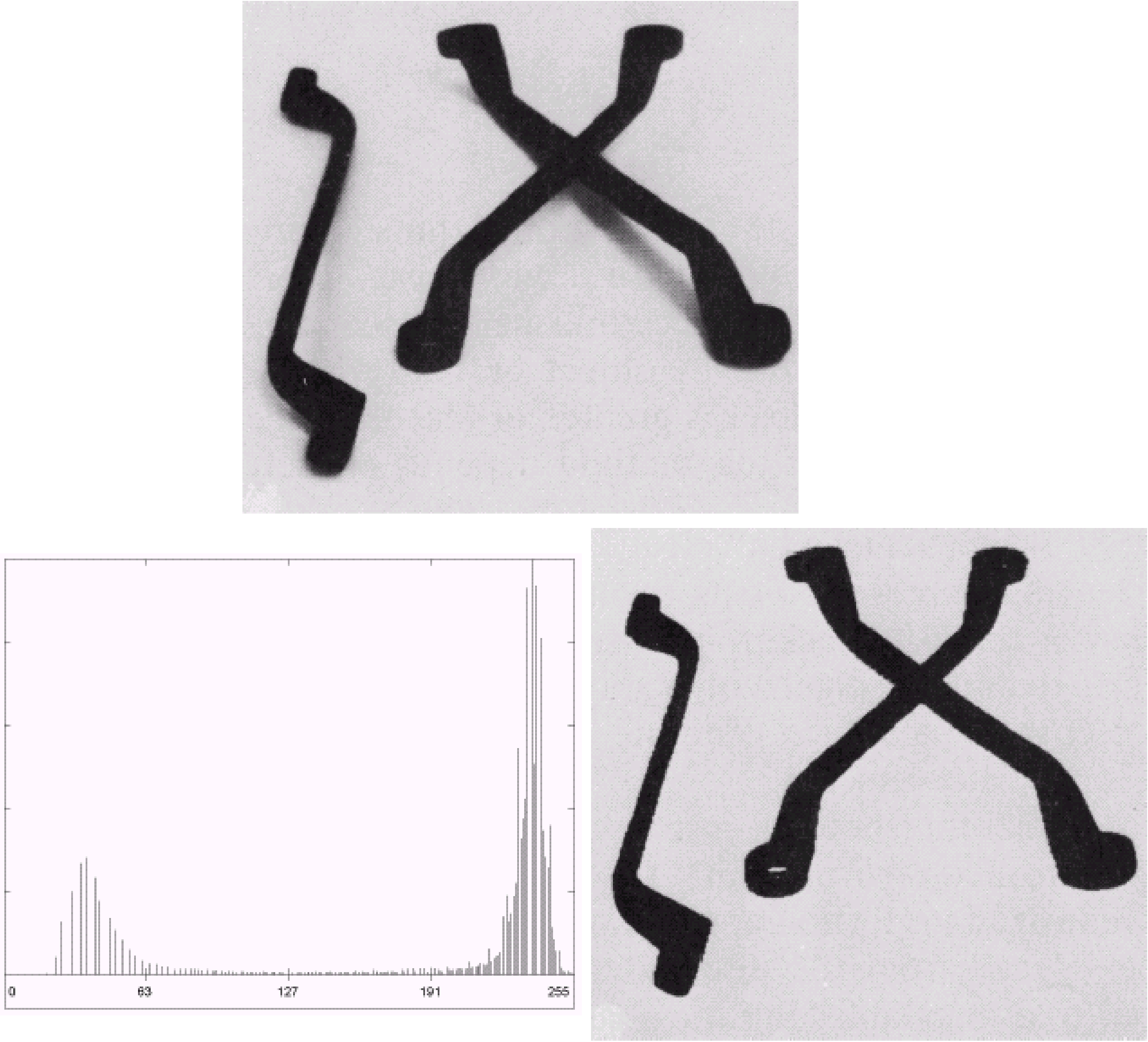
T = 102





After thresholding

Intensity Thresholding Example



a
b c

FIGURE 10.28 (a) Original image. (b) Image histogram. (c) Result of global thresholding with T midway between the maximum and minimum gray levels.

(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

Automatic Threshold Level Selection

The major problem of intensity thresholding is to find a good threshold level

Algorithm: effective for bimodal histogram

1. Set initial value of T

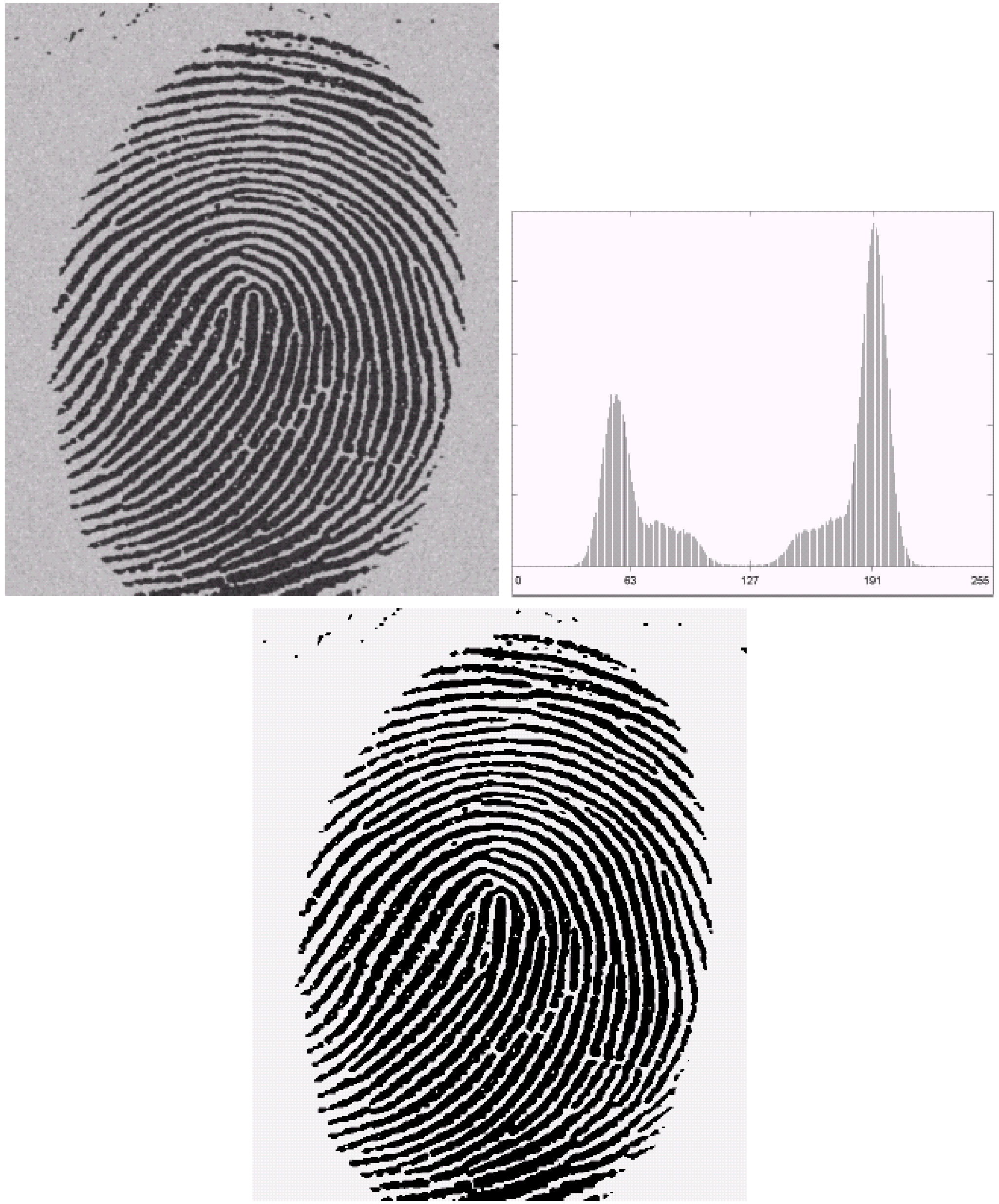
2. $$T_1 = Average\left(p(x,y) \middle| p(x,y) > T\right)$$

3. $$T_2 = Average\left(p(x,y) \middle| p(x,y) \le T\right)$$

4. $$T = \frac{T_1 + T_2}{2}$$

5. Repeat step 2

Automatic Threshold Level Selection Example



a b
c

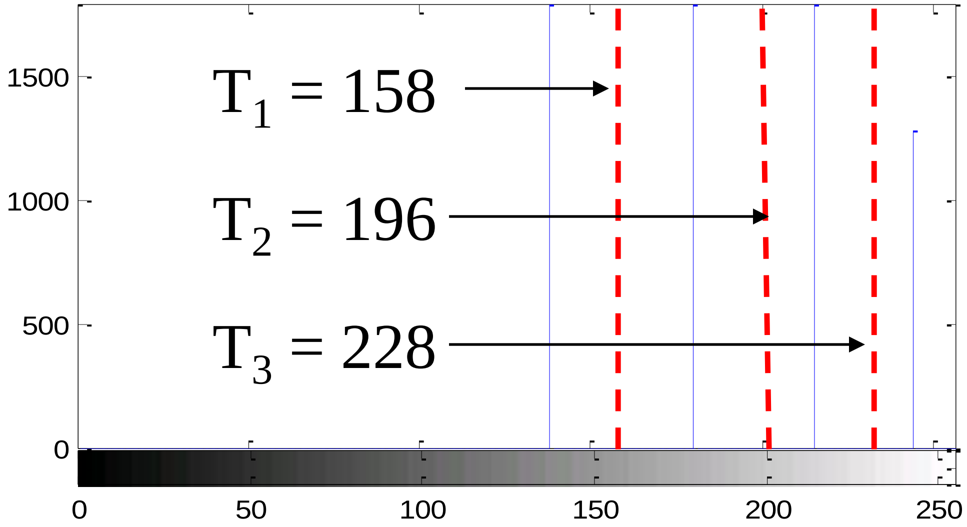
FIGURE 10.29 (a) Original image. (b) Image histogram. (c) Result of segmentation with the threshold estimated by iteration. (Original courtesy of the National Institute of Standards and Technology.)

(Images from Rafael C. Gonzalez and Richard E. Wood, Digital Image Processing, 2nd Edition.

Multilevel Intensity Thresholding

Threshold Level

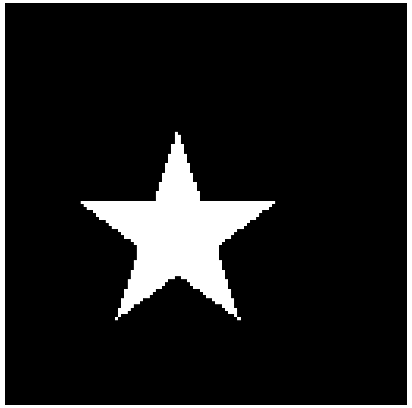
Histogram



$T_1 < P < T_2$

$T_2 < P < T_3$

$P > T_3$

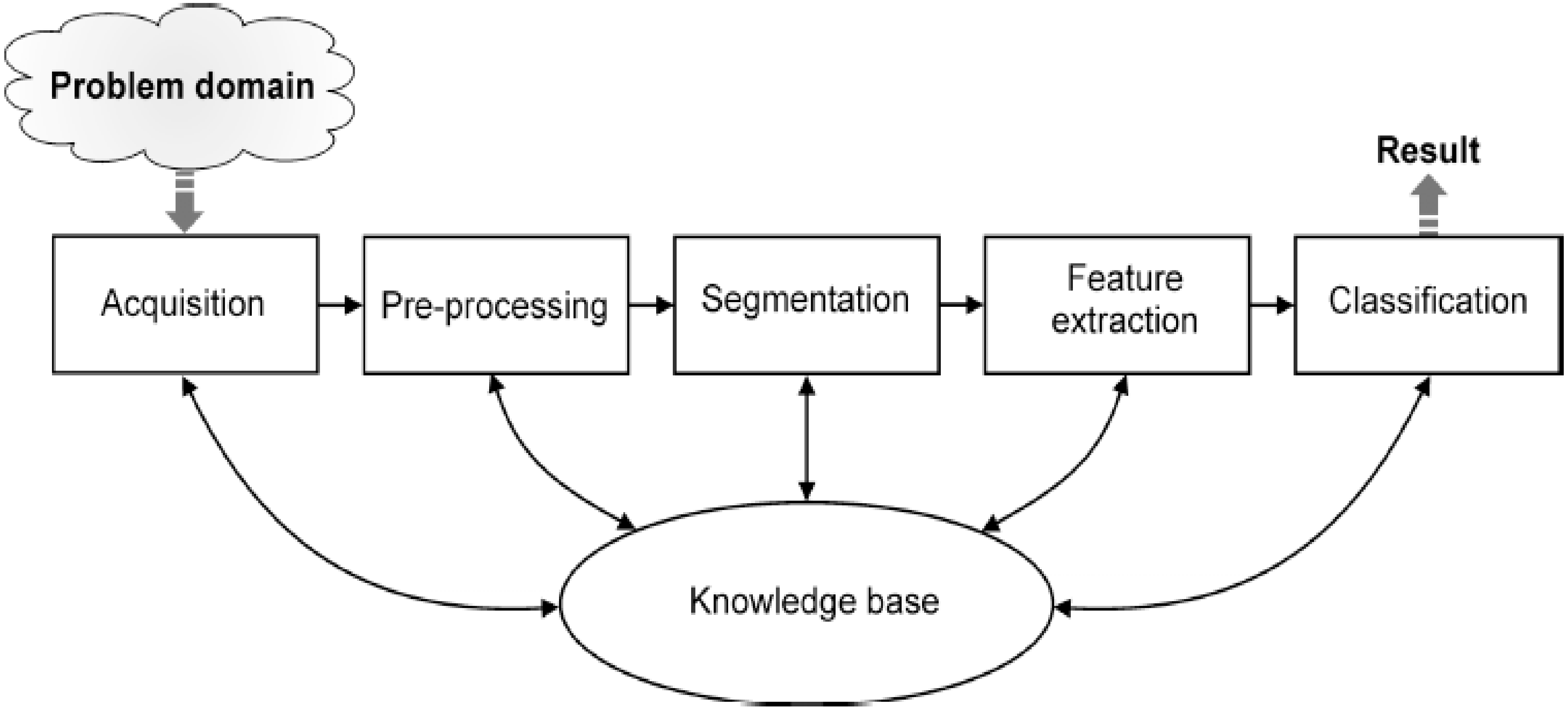


Medical Image Segmentation

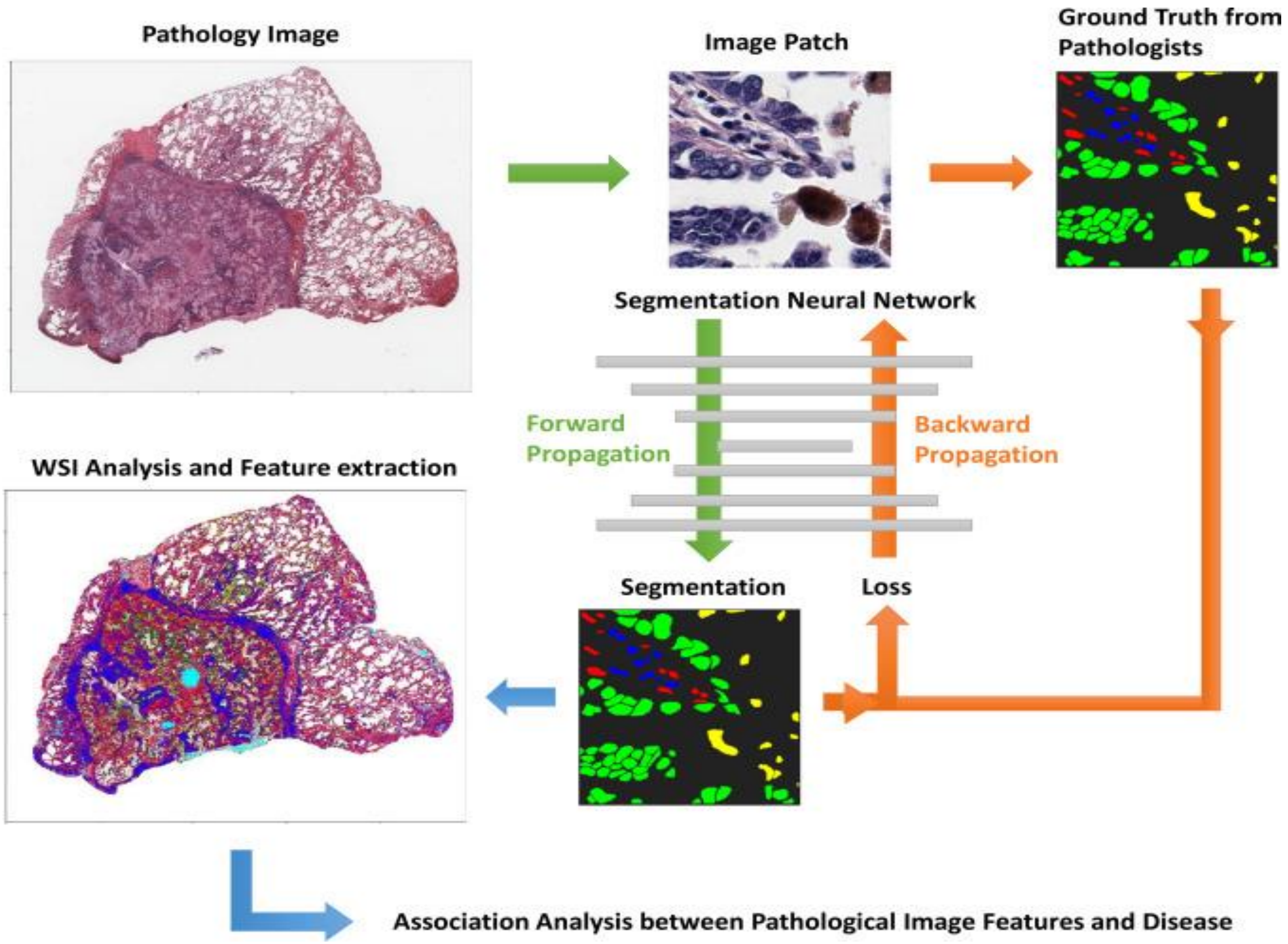
Medical image segmentation is a computer vision task that involves dividing a medical image into multiple segments, where each segment represents a different object or structure of interest in the image. This process is crucial for diagnosis, treatment planning, and quantitative analysis in the medical field. It can be a time-consuming task, but recent advances in artificial intelligence (AI) software techniques are making it easier, allowing for a more precise analysis and the removal of unwanted details from a scan. Various methods, including deep learning, convolutional neural networks, and machine learning algorithms, are being used for medical image segmentation, and they have shown promising results in terms of accuracy and efficiency

Introduction to Digital Image Segmentation

Machine Vision Systems



Pathology Image Segmentation



Radiology: image segmentation

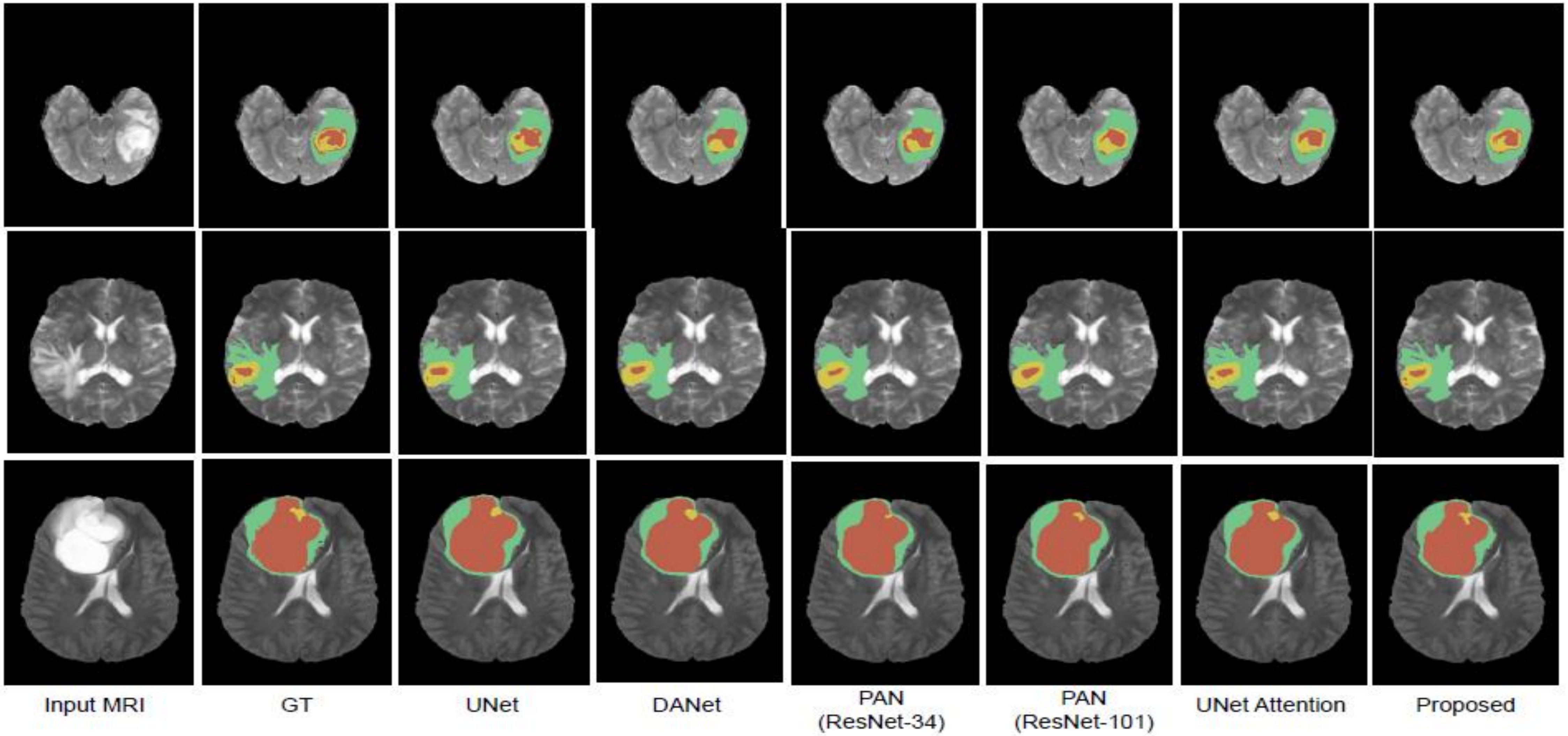


Fig. 5: Results on three subjects on the BRATS Challenge dataset. In these figures, the following tumor structures are depicted: oedema (green), enhancing core (yellow) and necrotic or tumor core (red).

classification of digital image segmentation algorithms

Digital Image segmentation employs two main approaches:

Similarity Approach:

Method: Detects similarity among image pixels using a specified threshold.

Application: Utilized by machine learning algorithms, such as clustering, to segment images.

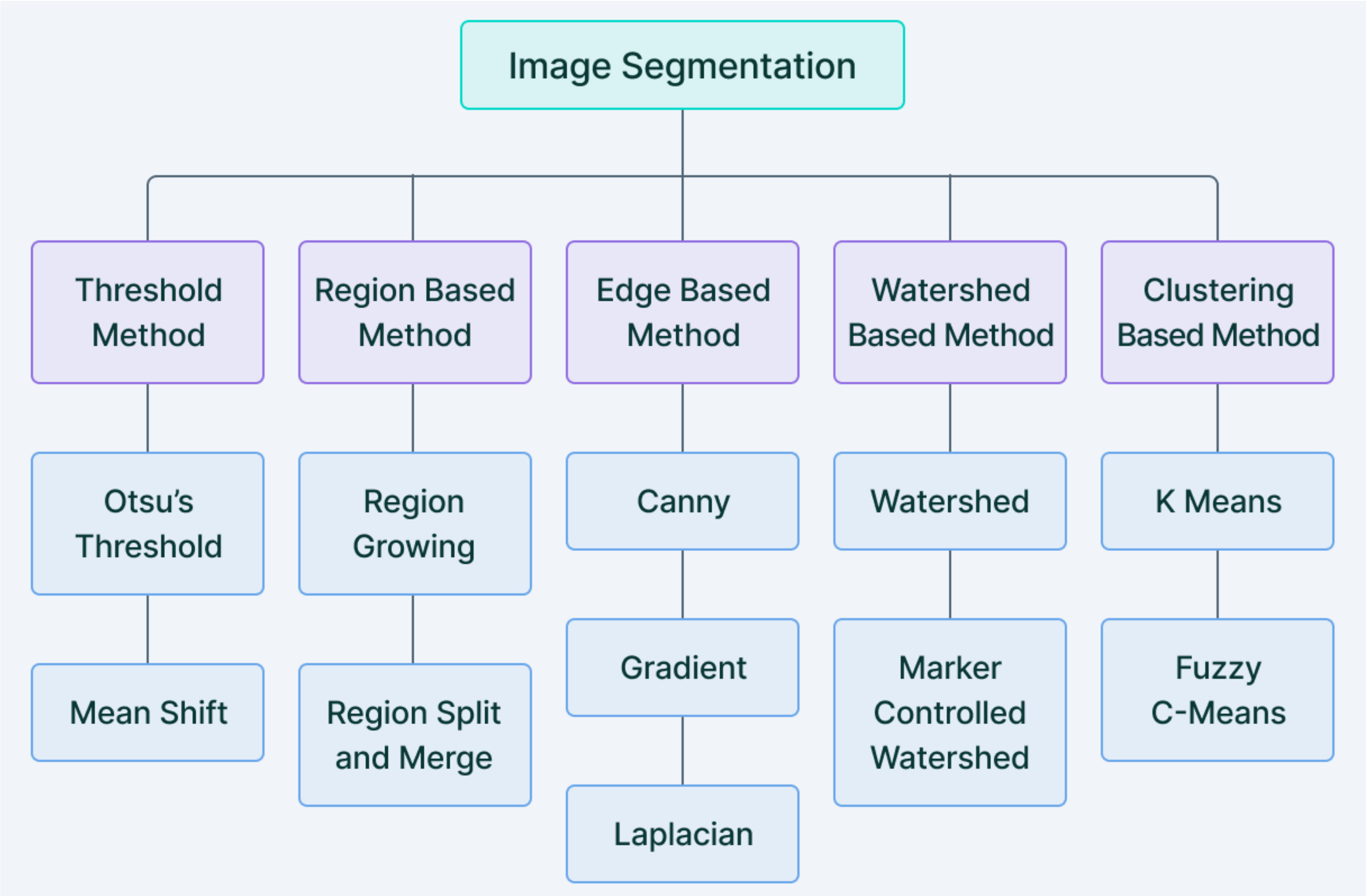
Discontinuity Approach:

Method: Relies on the discontinuity in pixel intensity values of the image.

Application: Employed by techniques like line, point, and edge detection,

producing intermediate segmentation results for further processing towards the final segmented image.

Image segmentation Techniques



- Threshold-based segmentation
- Edge-based image segmentation
- Region-based image segmentation
- Clustering-based image segmentation
- Artificial neural network-based segmentation

Automatic Image Segmentation

Automatic image segmentation, a key computer vision technique, divides digital images into segments for simplified analysis. Common approaches include:

Threshold-based Segmentation:

Method: Sets a threshold on pixel intensity to create binary or multi-color images.

Advantage: Simplicity.

Region-based Segmentation:

Method: Assigns labels based on pixel similarity to a seed pixel (user-defined).

Types: Region growing and region splitting and merging.

Advantage: User interaction.

Automatic Image Segmentation

Machine Learning-based Segmentation:

Method: Uses algorithms like clustering and deep learning to identify objects and segment images.

Examples: Graph cuts.

Advantage: Automation.

Graphical Energy Minimization Techniques:

Examples: GrabCut, utilizing Gaussian mixture models and graph cuts.

Use: Particularly for interactive segmentation.

Instance Segmentation:

Method: Identifies specific object instances for each pixel.

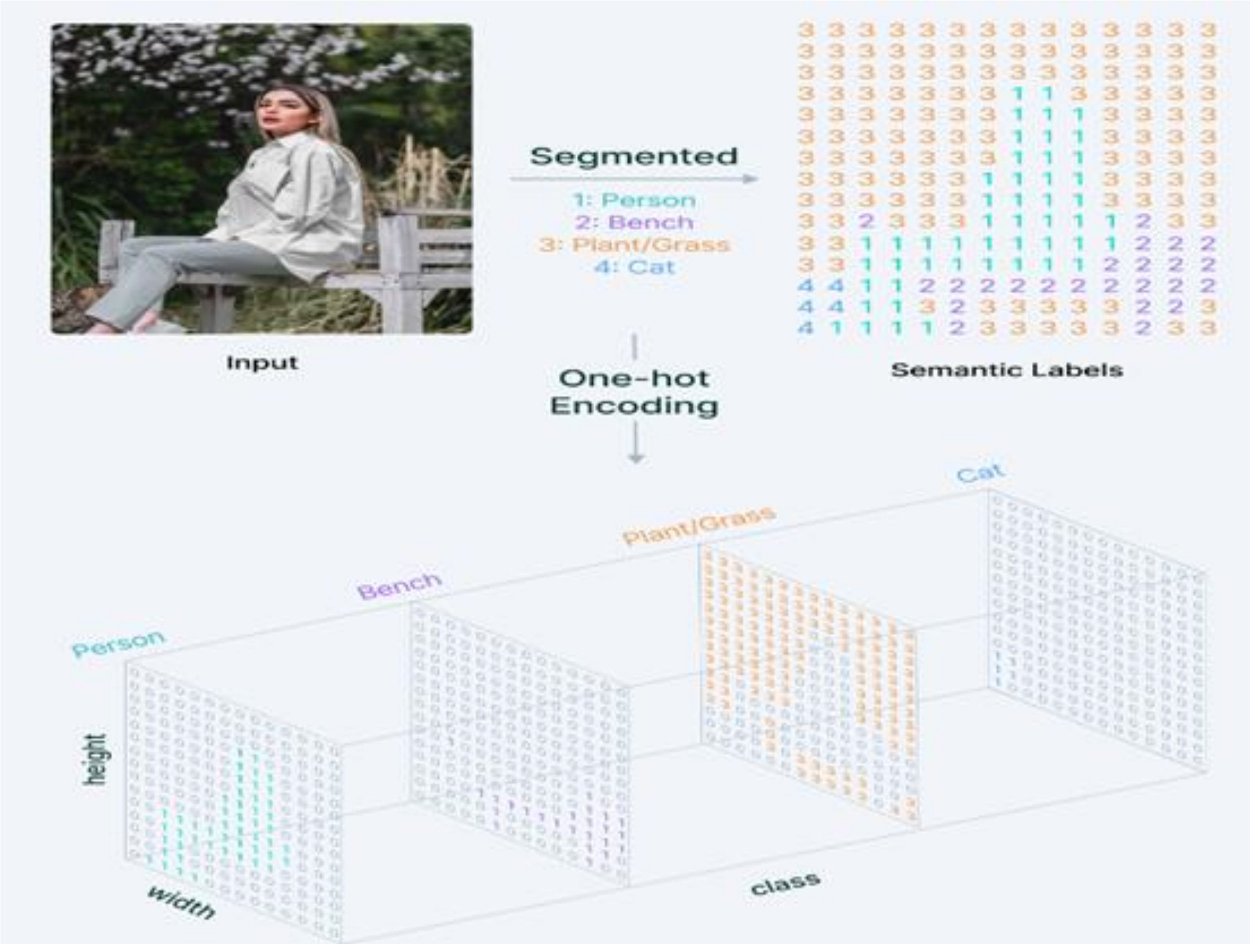
Use: Detects distinct objects of interest in the image.

Deep Learning-based methods

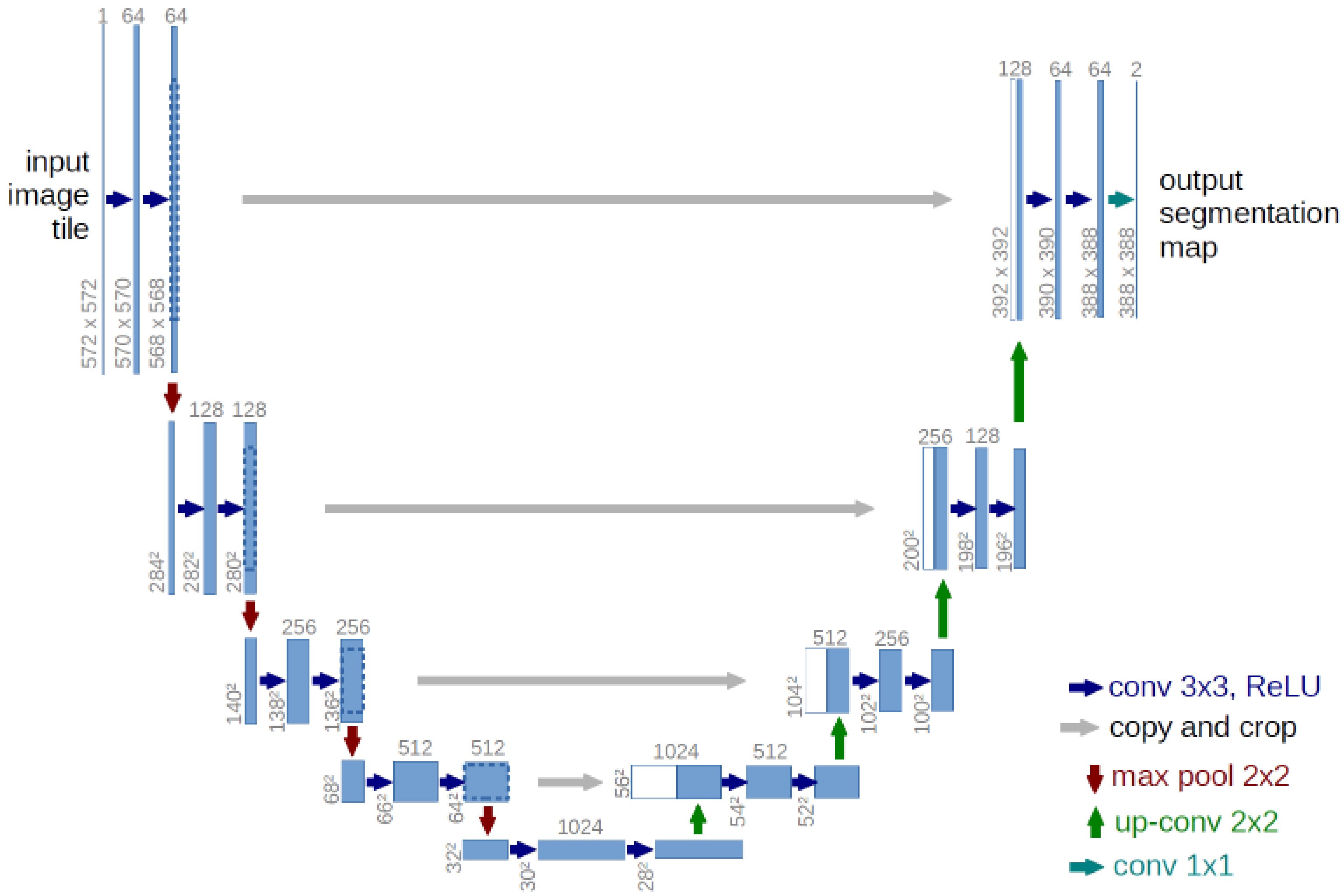
- Semantic segmentation models provide segment maps as outputs corresponding to the inputs they are fed.
- These segment maps are often n-channeled with n being the number of classes the model is supposed to segment. Each of these n-channels is binary in nature with object locations being “filled” with ones and empty regions consisting of zeros. The ground truth map is a single channel integer array the same size as the input and has a range of “n”, with each segment “filled” with the index value of the corresponding classes (classes are indexed from 0 to n-1).

Deep Learning-based methods

Sematic Segmentation



U-Net Segmentation Architecture:



U-Net Segmentation Architecture:

U-Net is a convolutional neural network architecture used for image segmentation, particularly in the biomedical imaging field. It takes an image as input and produces a pixel-wise segmentation map as output. The U-Net architecture consists of an encoder and a decoder. The encoder captures the context in the image through a series of convolutional and max-pooling layers, while the decoder combines the feature maps from the encoder with upsampled feature maps to generate the final segmentation. U-Net was initially developed to detect cell boundaries in biomedical images and has since been widely used in various medical image segmentation tasks due to its effectiveness in capturing fine details and spatial information

Architecture Overview:

Encoder-Decoder Structure: U-Net has an encoder-decoder setup; encoder captures context, decoder produces segmentation map.

Skip Connections: Connect corresponding layers, preserving fine details during upsampling.

Encoder:

Convolutional Blocks: Series of blocks with convolutional layers, batch normalization, and ReLU activation.

Downsampling: Uses max-pooling or strided convolutions to reduce spatial dimensions.

Decoder:

Upsampling: Employs techniques like transposed convolutions for spatial resolution restoration.

Concatenation: Skip connections concatenate feature maps, aiding in spatial detail recovery.

Skip Connections:

Purpose: Preserve high-res information during encoding and decoding.

Enhancement: Mitigate loss of spatial info during downsampling.

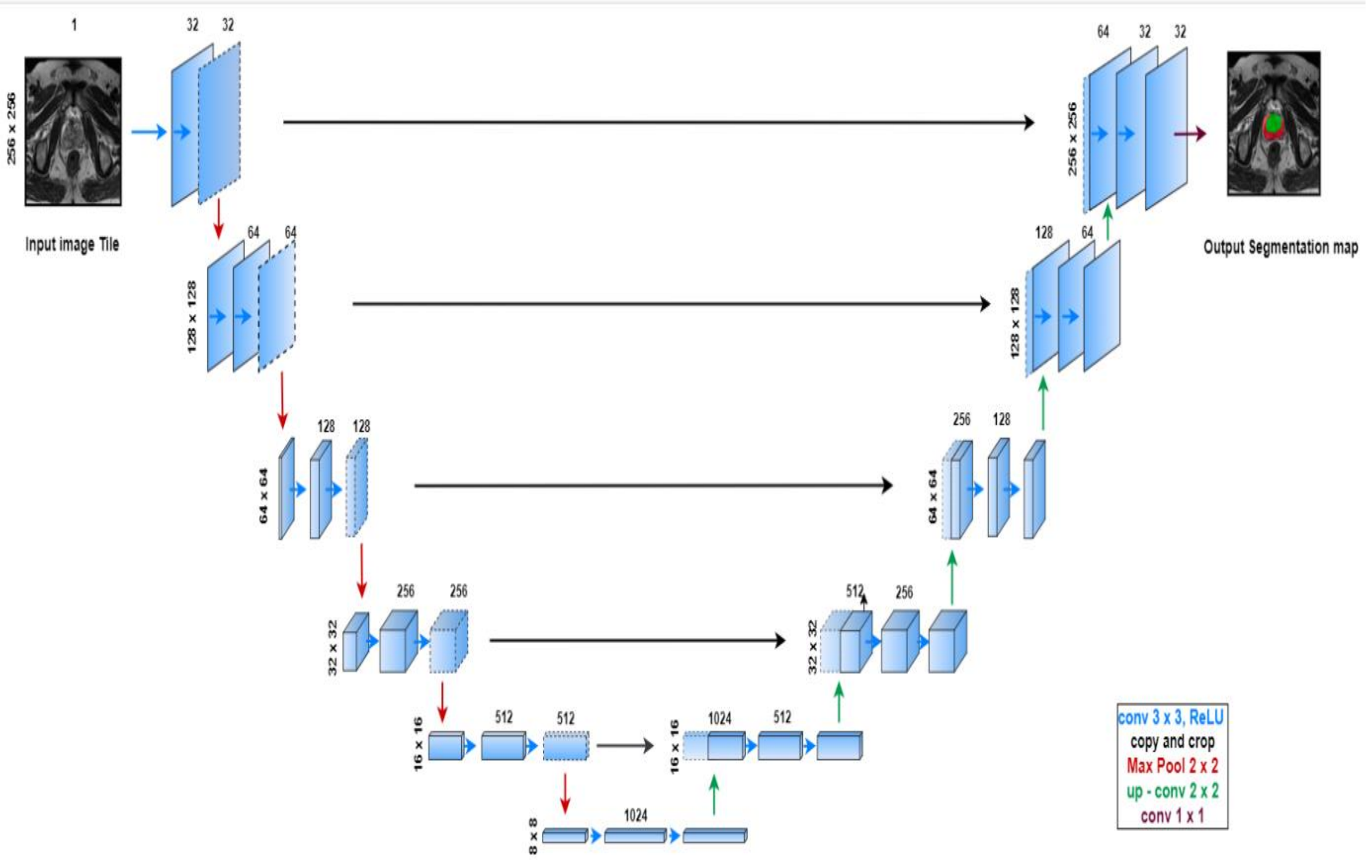
Output Layer:

Activation Function: Final layer often uses softmax for probability maps in segmentation tasks.

Loss Function:

Cross-Entropy Loss: Common choice for image segmentation tasks.

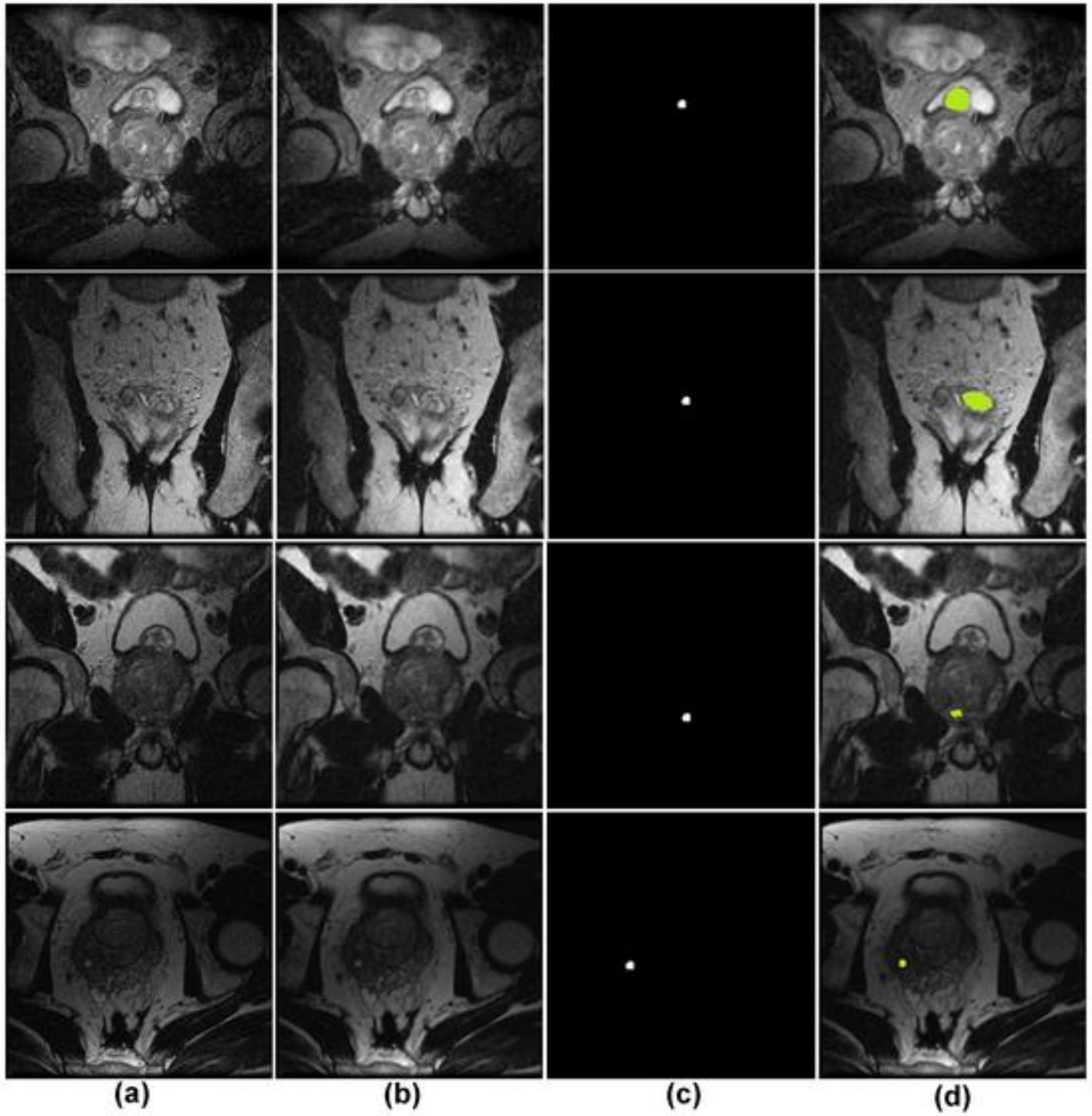
Architecture Overview of mpMRI segmentation:



Reference:
Gavade, Anil B., Rajendra Nerli, Neel Kanwal, Priyanka A. Gavade, Shridhar Sunilkumar Pol, and Syed Tahir Hussain Rizvi. 2023. "Automated Diagnosis of Prostate Cancer Using mpMRI Images: A Deep Learning Approach for Clinical Decision Support" Computers 12, no. 8: 152.
https://doi.org/10.3390/computers12080152
https://www.mdpi.com/2073-431X/12/8/152

Implementation Results:

Figure 6. Visualization of the region of interest (RoI) using our proposed UNet+LSTM DL approach. (**a**) Example mpMRI images; (**b**) preprocessed version of the images; (**c**) Ground truth; (**d**) map of predicted cancerous RoI.



Reference:

Gavade, Anil B., Rajendra Nerli, Neel Kanwal, Priyanka A. Gavade, Shridhar Sunilkumar Pol, and Syed Tahir Hussain Rizvi. 2023. "Automated Diagnosis of Prostate Cancer Using mpMRI Images: A Deep Learning Approach for Clinical Decision Support" Computers 12, no. 8: 152. https://doi.org/10.3390/computers12080152
https://www.mdpi.com/2073-431X/12/8/152

Q&A?

Thank you.