

# **Gray Level Co- occurrence Matrix (GLCM)**

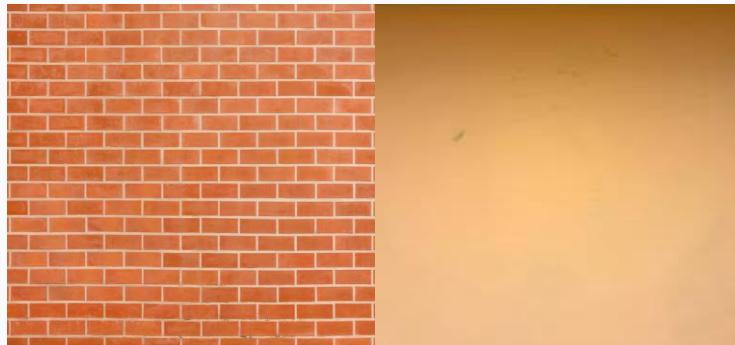
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CSE523 – Digital Image Processing

# Gray Level Co-occurrence (GLCM)

## Texture:

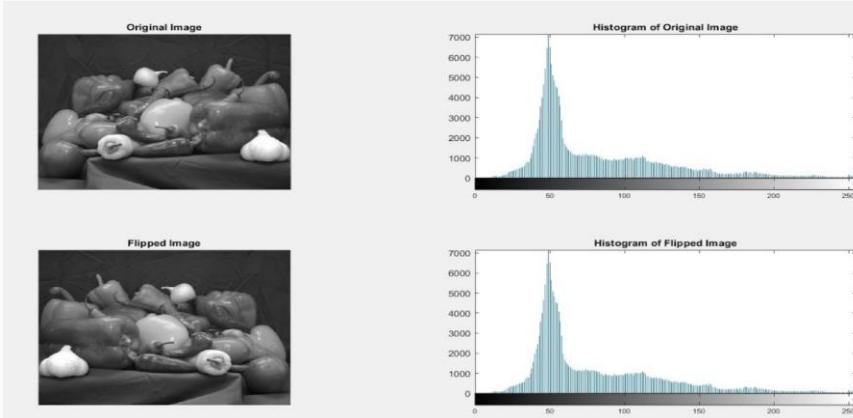
- ❑ Texture in an image means how a surface looks and feels visually – whether it appears smooth, rough, bumpy, or patterned.
- ❑ Texture comes from how pixel values change and repeat in a small area of the image.



# Gray Level Co-occurrence (GLCM)

## Background:

- ❑ An image histogram only counts how many times an intensity occurs, but not where it occurs.
- ❑ Many textures have similar histograms but different spatial patterns.



## Keynote:

Texture is determined not only by intensities but by their relationship.

# **Gray Level Co-occurrence (GLCM)**

## **Background:**

- ❑ By studying texture, a computer can understand what kind of surface is in an image.
- ❑ This helps in tasks like finding objects, separating regions, or identifying diseases in medical images.
- ❑ Methods like GLCM and LBP help computers measure these texture patterns automatically.

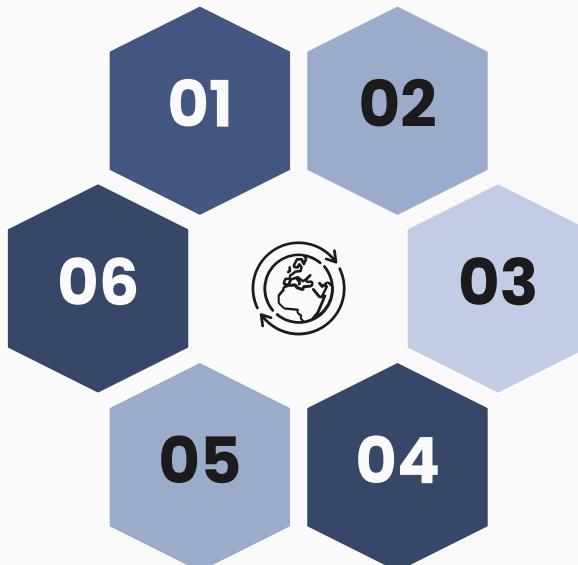
# Gray Level Co-occurrence (GLCM)

## GLCM:

- GLCM (Gray Level Co-occurrence Matrix) captures how often pairs of gray levels occur next to each other in a specific direction and distance.
- It encodes spatial relationships between pixels → good for texture analysis.
- It is simple and interpretable:
  - ❖ the matrix itself is just co-occurrence counts;
  - ❖ from it we derive well-known features (contrast, energy, homogeneity, correlation, etc.).

# Main Mechanism of GLCM

- Quantize gray levels
- Derive texture features
- Normalize to get probabilities



- Choose offset (distance + direction)
- Build the GLCM  $P(i,j)$
- Symmetrization

# Main mechanism of GLCM

Consider a grayscale image  $I(x,y)$  with gray levels  $0, 1, \dots, L - 1$ .

## Step 1: Quantize gray levels

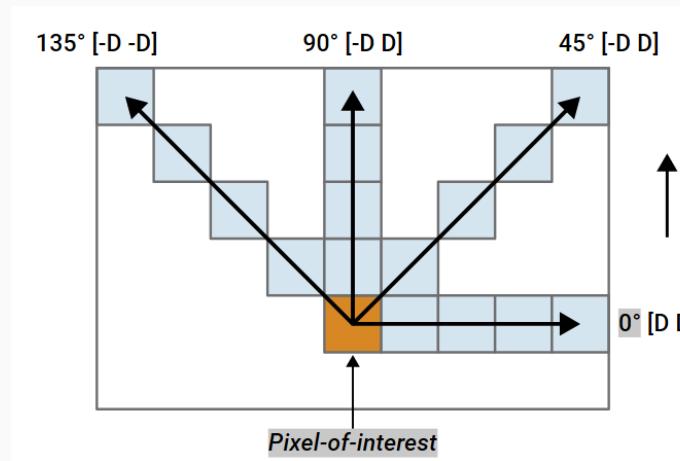
- ❑ For an 8-bit image (0–255), we might reduce it to, say,  $L = 16$  or  $L = 8$  levels to keep the matrix size manageable.
- ❑ After quantization, every pixel has value in  $\{0, 1, \dots, L - 1\}$ .
- ❑ Quantization formula:  $new\_pixel = \frac{old\_pixel}{Current\ range \div New\ range}$

$$I = \begin{bmatrix} 10 & 10 & 80 & 90 \\ 15 & 200 & 210 & 85 \\ 20 & 205 & 215 & 95 \\ 25 & 30 & 100 & 110 \end{bmatrix} \quad I_q = \begin{bmatrix} 0 & 0 & 1 & 1 \\ 0 & 3 & 3 & 1 \\ 0 & 3 & 3 & 1 \\ 0 & 0 & 1 & 1 \end{bmatrix} \quad L = 8 \text{ bit to } L = 4 \text{ bit}$$

# Main mechanism of GLCM

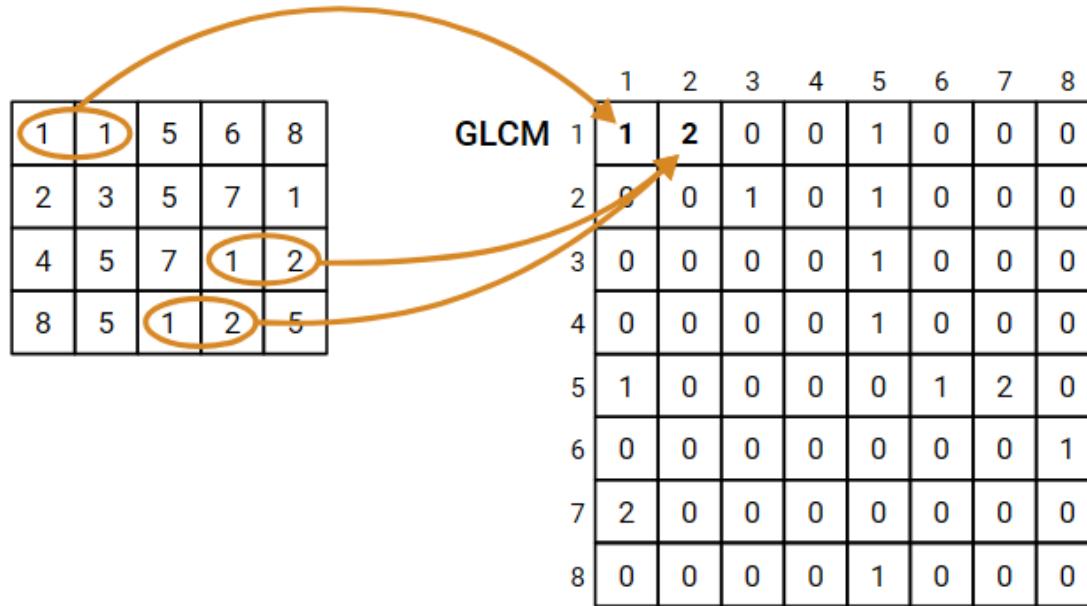
Step 2: Choose offset (distance + direction)

- ❑ Choose a distance  $d$  (e.g., 1 pixel, 2 pixels).
- ❑ Choose a direction  $\theta$  :



# Main mechanism of GLCM

Step 3: Build the GLCM  $P(i,j)$



# Main mechanism of GLCM

## Step 4: Symmetrization

- Sometimes we count both directions:
- If we also count pairs  $(j, i)$  reverse direction, we might define a symmetric GLCM:

$$Psym(i, j) = P(i, j) + P(j, i)$$

## Step 5: Normalize to get probabilities

- To derive features, we often normalize:

$$p(i, j) = \frac{P(i, j)}{\sum_{i,j} P(i, j)}$$

- so that  $\sum_{i,j} p(i, j) = 1$ .

# Main mechanism of GLCM

## Step 6: Derive texture features

From the normalized GLCM  $p(i, j)$ , classic features include:

- **Contrast:** measures local intensity variation

$$\text{Contrast} = \sum (i - j)^2 p(i, j)$$

- **Energy** (Angular Second Moment):

$$\text{Energy} = \sum_{i,j} p(i, j)^2$$

- **Homogeneity** (Inverse Difference Moment):

$$\text{Homogeneity} = \sum_{i,j} \frac{p(i, j)}{1 + |i - j|}$$

- **Correlation:** measures how correlated neighboring gray levels are.

# Example

We are given the  $4 \times 4$  image,

- ❑ distance  $d = 1$  pixel.
- ❑ Direction  $\theta = 0^\circ$  (right side)

|   |   |   |   |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |



| P(i,j) | 0     | 1     | 2     | 3     |
|--------|-------|-------|-------|-------|
| 0      | (0,0) | (0,1) | (0,2) | (0,3) |
| 1      | (1,0) | (1,1) | (1,2) | (1,3) |
| 2      | (2,0) | (2,1) | (2,2) | (2,3) |
| 3      | (3,0) | (3,1) | (3,2) | (3,3) |

# Example

Build the GLCM  $P(i,j)$

|   |   |   |   |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |

For 0,0

| $P(i,j)$ | 0 | 1 | 2 | 3 |
|----------|---|---|---|---|
| 0        | 2 |   |   |   |
| 1        |   |   |   |   |
| 2        |   |   |   |   |
| 3        |   |   |   |   |

# Example

Build the GLCM  $P(i,j)$

|   |   |   |   |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |

For 0,1

| $P(i,j)$ | 0 | 1 | 2 | 3 |
|----------|---|---|---|---|
| 0        | 2 | 2 |   |   |
| 1        |   |   |   |   |
| 2        |   |   |   |   |
| 3        |   |   |   |   |

# Example

Build the GLCM  $P(i,j)$

|   |   |   |   |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |

For 0,2

| $P(i,j)$ | 0 | 1 | 2 | 3 |
|----------|---|---|---|---|
| 0        | 2 | 2 | 1 |   |
| 1        |   |   |   |   |
| 2        |   |   |   |   |
| 3        |   |   |   |   |

# Example

Build the GLCM  $P(i,j)$

|   |   |   |   |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |

For 0,3

| $P(i,j)$ | 0 | 1 | 2 | 3 |
|----------|---|---|---|---|
| 0        | 2 | 2 | 1 | 0 |
| 1        |   |   |   |   |
| 2        |   |   |   |   |
| 3        |   |   |   |   |

# Example

Build the GLCM  $P(i,j)$

|   |   |   |   |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |

For 1,0

| $P(i,j)$ | 0 | 1 | 2 | 3 |
|----------|---|---|---|---|
| 0        | 2 | 2 | 1 | 0 |
| 1        | 0 |   |   |   |
| 2        |   |   |   |   |
| 3        |   |   |   |   |

# Example

Build the GLCM  $P(i,j)$

|   |   |   |   |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |

For 1,1

| $P(i,j)$ | 0 | 1 | 2 | 3 |
|----------|---|---|---|---|
| 0        | 2 | 2 | 1 | 0 |
| 1        | 0 | 2 |   |   |
| 2        |   |   |   |   |
| 3        |   |   |   |   |

# Example

Build the GLCM  $P(i,j)$

|   |   |   |   |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |

For 1,2

| $P(i,j)$ | 0 | 1 | 2 | 3 |
|----------|---|---|---|---|
| 0        | 2 | 2 | 1 | 0 |
| 1        | 0 | 2 | 0 |   |
| 2        |   |   |   |   |
| 3        |   |   |   |   |

# Example

Build the GLCM  $P(i,j)$

|   |   |   |   |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |

For 1,3

| $P(i,j)$ | 0 | 1 | 2 | 3 |
|----------|---|---|---|---|
| 0        | 2 | 2 | 1 | 0 |
| 1        | 0 | 2 | 0 | 0 |
| 2        |   |   |   |   |
| 3        |   |   |   |   |

# Example

Build the GLCM  $P(i,j)$

|   |   |   |   |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |



| $P(i,j)$ | 0 | 1 | 2 | 3 |
|----------|---|---|---|---|
| 0        | 2 | 2 | 1 | 0 |
| 1        | 0 | 2 | 0 | 0 |
| 2        | 0 | 0 | 3 | 1 |
| 3        | 0 | 0 | 0 | 1 |

# Example

Symmetrization

|   |   |   |   |
|---|---|---|---|
| 2 | 2 | 1 | 0 |
| 0 | 2 | 0 | 0 |
| 0 | 0 | 3 | 1 |
| 0 | 0 | 0 | 1 |



CM of the image

|   |   |   |   |
|---|---|---|---|
| 2 | 0 | 0 | 0 |
| 2 | 2 | 0 | 0 |
| 1 | 0 | 3 | 0 |
| 0 | 0 | 1 | 1 |

Transpose CM of the image



|   |   |   |   |
|---|---|---|---|
| 4 | 2 | 1 | 0 |
| 2 | 4 | 0 | 0 |
| 1 | 0 | 6 | 1 |
| 0 | 0 | 1 | 2 |

Symmetric GLCM

# Example

Normalization

Sum of all elements = 24

|   |   |   |   |
|---|---|---|---|
| 4 | 2 | 1 | 0 |
| 2 | 4 | 0 | 0 |
| 1 | 0 | 6 | 1 |
| 0 | 0 | 1 | 2 |

Symmetric GLCM



|        |       |        |        |
|--------|-------|--------|--------|
| 0.167  | 0.083 | 0.0416 | 0      |
| 0.083  | 0.167 | 0      | 0      |
| 0.0416 | 0     | 0.25   | 0.0416 |
| 0      | 0     | 0.0416 | 0.083  |

Normalized GLCM

# Example

Contrast

| P(i,j) | 0 | 1 | 2 | 3 |
|--------|---|---|---|---|
| 0      | 0 | 1 | 4 | 9 |
| 1      | 1 | 0 | 1 | 4 |
| 2      | 4 | 1 | 0 | 1 |
| 3      | 9 | 4 | 1 | 0 |

$$|I - J|^2$$



|        |       |        |        |
|--------|-------|--------|--------|
| 0.167  | 0.083 | 0.0416 | 0      |
| 0.083  | 0.167 | 0      | 0      |
| 0.0416 | 0     | 0.25   | 0.0416 |
| 0      | 0     | 0.0416 | 0.083  |

$$\text{Normalized GLCM } p(i,j)$$

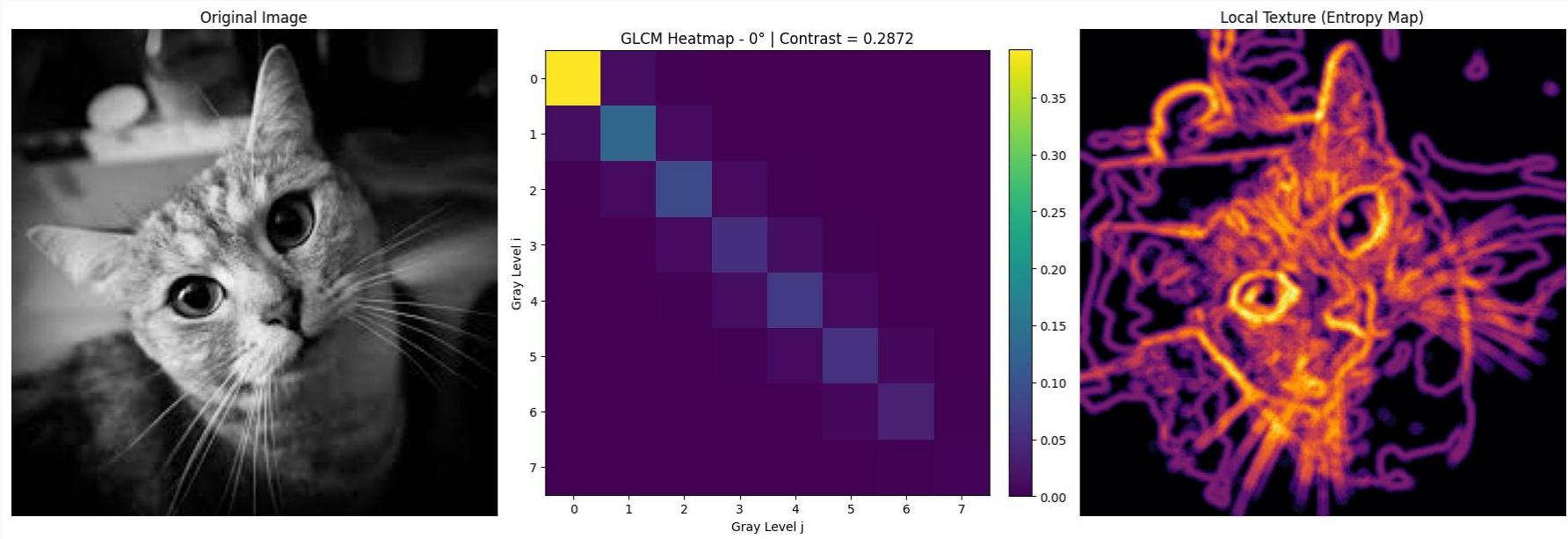


$$\text{Contrast} = 0.582$$

|        |       |        |        |
|--------|-------|--------|--------|
| 0      | 0.083 | 0.1664 | 0      |
| 0.083  | 0     | 0      | 0      |
| 0.1664 | 0     | 0      | 0.0416 |
| 0      | 0     | 0.0416 | 0      |

$$|I - J|^2 \times p(i,j)$$

# Example



# Advantages of GLCM

- ❑ Captures texture, not just intensity
  - ❖ Considers pairs of pixels → encodes spatial structure, helpful for distinguishing textures with similar histograms.
- ❑ Flexible
  - ❖ You can choose different directions and distances to capture anisotropic textures (e.g., vertical stripes vs horizontal stripes).
- ❑ Interpretable features
  - ❖ Features like contrast, energy, and homogeneity have intuitive meanings (rough vs smooth, homogeneous vs heterogeneous).

# Limitations of GLCM

- ❑ Parameter sensitivity
  - ❑ Results depend on:
    - ❖ Number of gray levels  $L$  (quantization),
    - ❖ Choice of distance  $d$ ,
    - ❖ Choice of directions ( $0^\circ, 45^\circ, 90^\circ, 135^\circ$ , etc.).
- ❑ High dimensionality for many gray levels
  - ❖ For an 8-bit image with 256 gray levels, GLCM is  $256 \times 256 \rightarrow 65,536$  entries per direction and distance → heavy in memory and computation.
- ❑ Not inherently rotation/scale invariant
  - ❖ Changing the rotation of the image changes the GLCM unless you average over multiple directions.

# Limitations of GLCM

- ❑ Sensitive to noise and illumination changes
  - ❖ Small changes in intensities (noise, illumination) can affect co-occurrence counts.
- ❑ Global unless localized
  - ❖ A single GLCM for the whole image may miss local variations; often people compute GLCM over moving windows, which increases computation.

# Applications of GLCM

- ❑ Medical Imaging
  - ❖ Tumor vs normal tissue classification in CT, MRI, ultrasound, histopathology, etc. GLCM features often help characterize tissue heterogeneity.
- ❑ Remote Sensing and Land Cover Classification
  - ❖ Distinguish forests, urban areas, water bodies based on texture in satellite images.
- ❑ Industrial Inspection
  - ❖ Detect surface defects (scratches, cracks, fabric defects, paper quality, etc.) from textures.
- ❑ Object Detection & Pattern Recognition
  - ❖ Use GLCM features as inputs to machine learning models for object detection, texture classification, etc.

# **Local Binary Pattern (LBP)**

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CSE523 – Digital Image Processing

# Local Binary Pattern (LBP)

LBP:

- ❑ Examine a pixel relative to its neighborhood:
  - ❖ Compare neighbor values to center pixel
  - ❖ Form binary pattern indicating structure
- ❑ It tells - are neighbors brighter or darker than the center?
- ❑ This effectively captures: Edges, Corners, Spots, Flat regions, Micro-texture.

# Main mechanism of LBP

Consider a grayscale image  $I(x,y)$

Step 1: Neighborhood (3×3 window)

|       |       |       |
|-------|-------|-------|
| $P_0$ | $P_1$ | $P_2$ |
| $P_7$ | $P_c$ | $P_3$ |
| $P_6$ | $P_5$ | $P_4$ |

# Main mechanism of LBP

Step 2:  $s(p_k - p_c)$

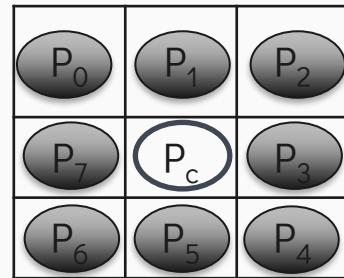
|                |                |                |
|----------------|----------------|----------------|
| P <sub>0</sub> | P <sub>1</sub> | P <sub>2</sub> |
| P <sub>7</sub> | P <sub>c</sub> | P <sub>3</sub> |
| P <sub>6</sub> | P <sub>5</sub> | P <sub>4</sub> |

Step 3: Binary decision

$$s(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$$

# Main mechanism of LBP

Step 2:  $s(p_k - p_c)$



Step 3: Binary decision

$$s(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$$

# Main mechanism of LBP

Step 4:  $2^k$  matrix

The diagram illustrates the mapping from a 3x3 neighborhood matrix to a 3x3 binary matrix. On the left, a 3x3 grid contains powers of 2 in its top-left and bottom-right corners, and a central cell labeled  $P_c$ . An arrow points from this grid to a 3x3 binary matrix on the right, where each cell's value is determined by the sign of the difference between the central cell and its neighbors.

|       |       |       |
|-------|-------|-------|
| $2^0$ | $2^1$ | $2^2$ |
| $2^7$ | $P_c$ | $2^3$ |
| $2^6$ | $2^5$ | $2^4$ |

→

|     |       |    |
|-----|-------|----|
| 1   | 2     | 4  |
| 128 | $P_c$ | 8  |
| 64  | 32    | 16 |

Step 5: LBP encoding

$$LBP(pc) = \sum_{k=0}^{k=7} s(p_{kc} - p_c) \cdot 2^k$$

# Example

Consider a grayscale image  $I(x,y)$

Step 1: Neighborhood (3×3 window)

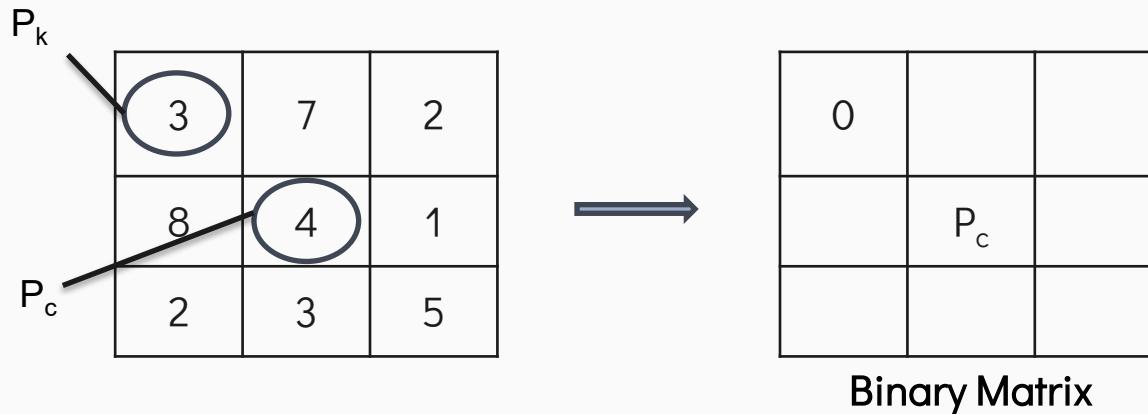
|   |   |   |
|---|---|---|
| 3 | 7 | 2 |
| 8 | 4 | 1 |
| 2 | 3 | 5 |

A 3x3 grid representing a neighborhood window. The center cell contains the value 4, which is circled in blue. A diagonal line labeled  $P_c$  points from the top-right corner of the grid towards the circled value 4.

# Example

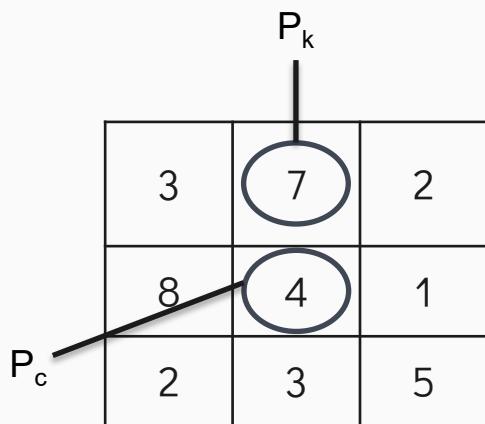
Step 2:  $s(p_k - p_c)$

$$s(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$$



# Example

Step 2:  $s(p_k - p_c)$



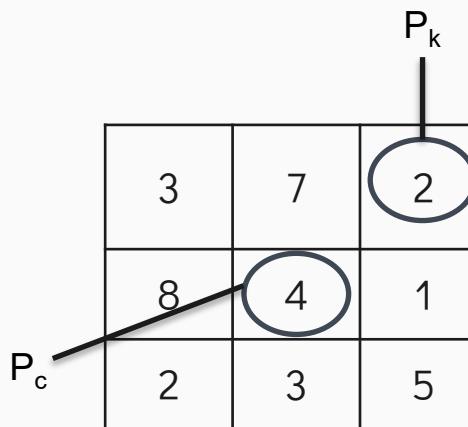
$$s(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$$

|   |     |  |
|---|-----|--|
| 0 | 1   |  |
|   | P_c |  |
|   |     |  |

Binary Matrix

# Example

Step 2:  $s(p_k - p_c)$



$$s(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$$

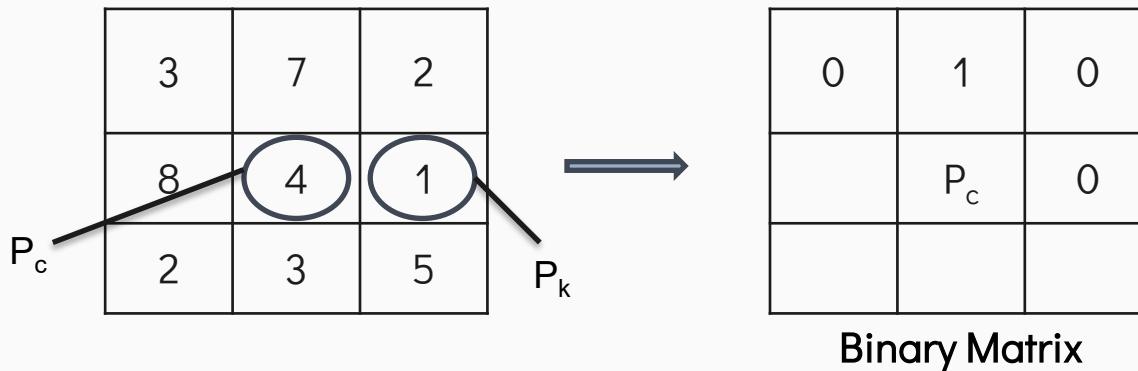
|   |                |   |
|---|----------------|---|
| 0 | 1              | 0 |
|   | P <sub>c</sub> |   |
|   |                |   |

Binary Matrix

# Example

Step 2:  $s(p_k - p_c)$

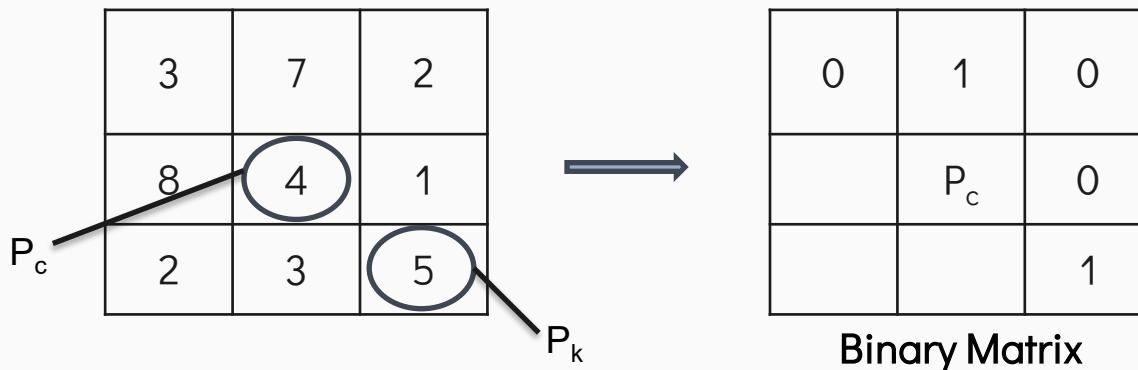
$$s(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$$



# Example

Step 2:  $s(p_k - p_c)$

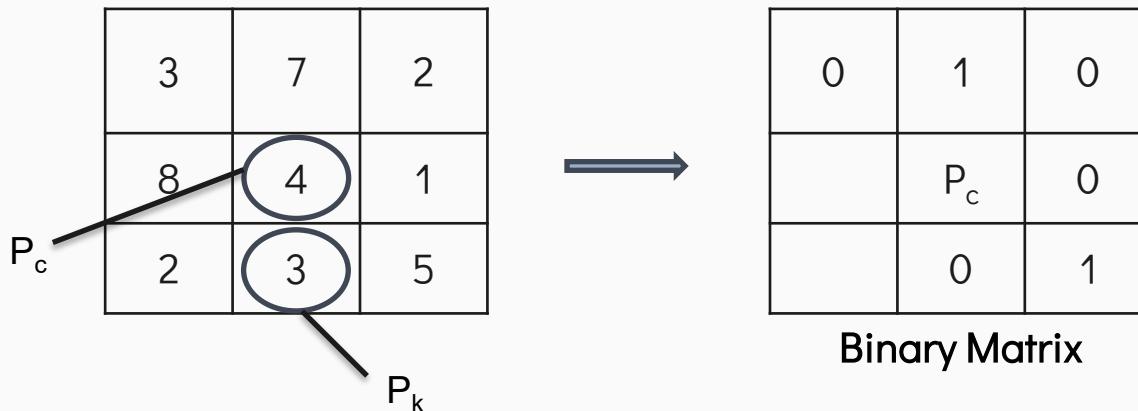
$$s(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$$



# Example

Step 2:  $s(p_k - p_c)$

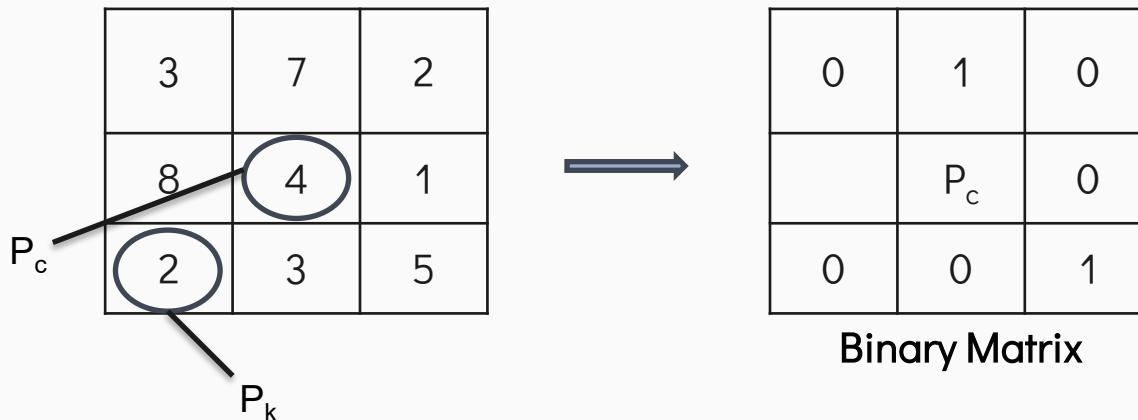
$$s(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$$



# Example

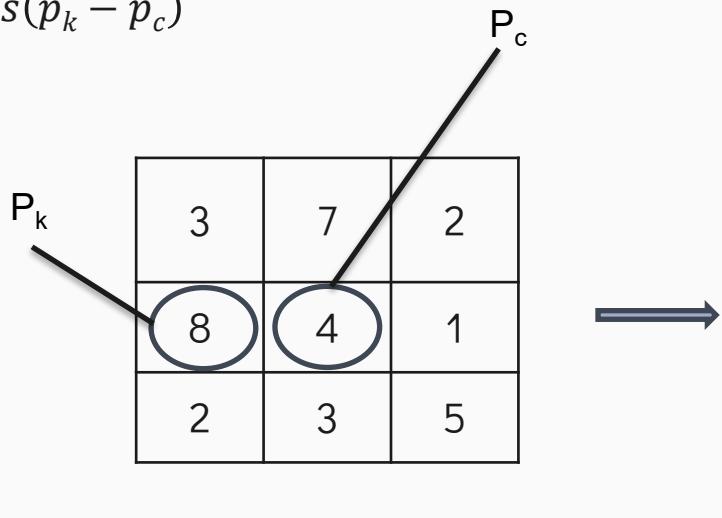
Step 2:  $s(p_k - p_c)$

$$s(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$$



# Example

Step 2:  $s(p_k - p_c)$



$$s(x) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases}$$

|   |       |   |
|---|-------|---|
| 0 | 1     | 0 |
| 1 | $P_c$ | 0 |
| 0 | 0     | 1 |

Binary Matrix

# Example

Step 2:  $s(p_k - p_c)$

|   |   |   |
|---|---|---|
| 3 | 7 | 2 |
| 8 | 4 | 1 |
| 2 | 3 | 5 |



|   |       |   |
|---|-------|---|
| 0 | 1     | 0 |
| 1 | $P_c$ | 0 |
| 0 | 0     | 1 |

Binary Matrix

# Example

Step 3: LBP encoding

|   |                |   |
|---|----------------|---|
| 0 | 1              | 0 |
| 1 | P <sub>c</sub> | 0 |
| 0 | 0              | 1 |



Binary Matrix

|     |                |    |
|-----|----------------|----|
| 1   | 2              | 4  |
| 128 | P <sub>c</sub> | 8  |
| 64  | 32             | 16 |

2<sup>k</sup> matrix



|     |                |    |
|-----|----------------|----|
| 0   | 2              | 0  |
| 128 | P <sub>c</sub> | 0  |
| 0   | 0              | 16 |

LBP

# Example

Step 3: LBP encoding

|   |                |   |
|---|----------------|---|
| 0 | 1              | 0 |
| 1 | P <sub>c</sub> | 0 |
| 0 | 0              | 1 |



Binary Matrix

|     |                |    |
|-----|----------------|----|
| 1   | 2              | 4  |
| 128 | P <sub>c</sub> | 8  |
| 64  | 32             | 16 |

2<sup>k</sup> matrix



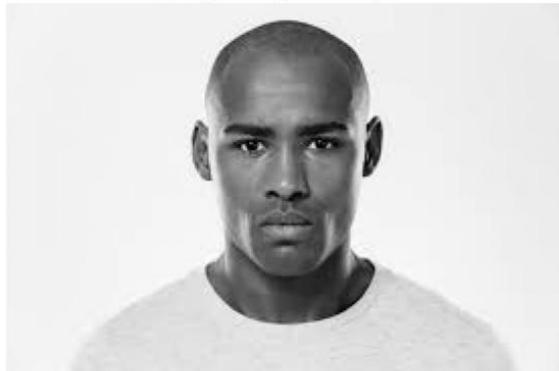
$$\sum_{i=0}^n 2 + 128 + 16 = 146$$

|     |                |    |
|-----|----------------|----|
| 0   | 2              | 0  |
| 128 | P <sub>c</sub> | 0  |
| 0   | 0              | 16 |

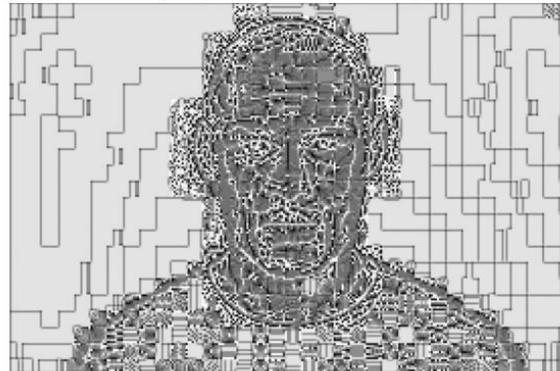
LBP

# Example

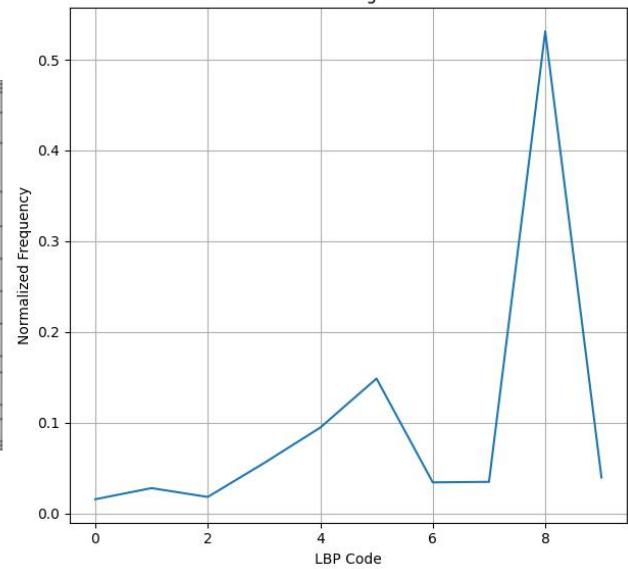
Original Grayscale Image



LBP Image  
(P=8, R=1, method='uniform')



LBP Histogram



# **Local Feature → Global Representation**

- ❑ After computing LBP for every pixel, we obtain a texture map.
- ❑ We extract a histogram of LBP values
- ❑ Histogram becomes the final feature vector used for:
  - ❖ Classification
  - ❖ Segmentation
  - ❖ Recognition
  - ❖ Anomaly detection

# **Advantages of LBP**

- ❑ Very fast and simple to compute.
- ❑ Works well even when lighting changes (brightness/contrast changes).
- ❑ Captures local texture patterns like edges, corners, and spots.
- ❑ Produces features that are easy to use in machine learning.
- ❑ Low memory usage → suitable for real-time systems

# Limitations of LBP

- ❑ Sensitive to noise, especially in flat or low-contrast areas.
- ❑ Only captures local information → misses global or large-scale patterns.
- ❑ Standard LBP is not rotation-invariant unless improved versions are used.
- ❑ Binary thresholding ( $\geq$  or  $<$ ) may lose fine intensity differences.
- ❑ Histogram features can become large if many neighborhoods are used

# **Applications of LBP**

- ❑ Face recognition (LBPH algorithm).
- ❑ Medical image analysis – detecting tumors or abnormal tissue textures.
- ❑ Industrial inspection – detecting cracks, scratches, or surface defects.
- ❑ Surveillance – human and object detection.
- ❑ Remote sensing – land-use and vegetation texture classification.
- ❑ Document analysis – paper texture and print quality recognition.
- ❑ Agricultural imaging – plant disease texture detection

# Comparison

## □ LBP vs GLCM Features

| Feature Type          | LBP          | GLCM                    |
|-----------------------|--------------|-------------------------|
| Complexity            | Low          | Medium                  |
| Uses Local Info?      | ✓            | ✓                       |
| Histogram size        | Small-medium | Depends on L, D, angles |
| Dataset size required | Small        | Small                   |
| Explainability        | High         | Medium                  |

# Thanks!

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