Texture: property of a group pixel/area. It is scale dependent. **How to describe:** Coarseness, Roughness, Direction, Uniformity, Density. **Statistical Texture** (grayscale intensities or colours. Less intuitive, but applicable to all images and computationally efficient. *Edge Density and Direction*) **and Structural Texture** (brick pattern, as a grammar).
Why is texture detection important? After learning edges,corners,etc, we want to check at a high level. Which leads us to detect objects with different attributes easier.
What are some challenges detecting texture? View point, scale dependencies, not unique for all cases.

Gray Level Run-Length Matrix (GLRLM): Pixels having the same grey level, in the same direction. Y_axis [pixels] X_axis[diameter]
Gray Level Co-occurrence Matrix (GLCM): quantifies texture by calculating how often pairs of pixel intensities occur at a specific spatial relationship in an image. X/Y_axis [pixles]
How it calculates texture: It computes matrices for pixel intensity pairs at varying angles and distances, capturing spatial patterns and relationships.
Issues with GLCM: High computational cost and sensitivity to image resolution, angle, and noise can limit its robustness.
Better for classification, as GLCM-derived features are effective for differentiating texture types but less suited for precise boundary detection in segmentation.
GLCM Contrast: $\sum P_{i,j} * (i-j)^2$ **Dissimilarity:** $\sum P_{i,j} * |i-j|$
IDM: $\sum P_{i,j} / (1+(i-j)^2)$ IDM has smaller numbers for images with high contrast, larger numbers for images low contrast

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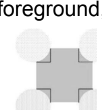
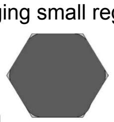
Law's Texture Energy Features [Level,Ripple,Edge,Spot,Wave]
L5 = [1,4,6,4,1] E5= [-1, -2, 0, 2, 1] S5= [-1, 0, 2, 0, -1] R5= [1, -4, 6, -4, 1] W5= [-1, 2, 0, -2, -1] These features help in distinguishing different textures by quantifying the energy in various texture patterns within an image.

Polar FFT. Fourier transform gives information about the entire image for all frequencies (scales) and orientation. This might not be useful for local textures. Fourier transform gives information about the entire image for all frequencies (scales) and orientation. This might not be useful for local textures.
Statistical approach: GLCM GLRL Simple to implement and effective for a wide range of textures. May not capture periodic patterns well.
Spectral approach: Law, FT Gabour Effective for detecting regular, repetitive textures. Computationally intensive and may require preprocessing.

Morphological image processing: is used to extract image components for representation and description of region shape, such as boundaries, skeletons, etc. rely on the relative ordering of pixel values, not on their numerical values, good for binary images. Dilation hit Erosion fit
Opening (A-B)+B -> Erosion followed by Dilation: remove small, isolated objects from the foreground of an image, placing them in the background. smooth the contour of a binary object and break narrow joining regions in an object.
Closing (A+B)-B -> Dilation Followed by Erosion: tends to remove small holes in the foreground, changing small regions of background into foreground

close -  open 

If erosion eliminates an object, dilation cannot recover it – dilation needs at least one foreground pixel to operate.
Thinning iterated = Skeletonization
Opening: Smooths object boundaries by removing small protrusions and separating close objects.
Closing: Fills small holes and gaps, connecting nearby objects in an image.
Dilation: Expands object boundaries, making objects appear larger and filling gaps.
Erosion: Shrinks object boundaries, removing small details and noise.
Thinning: Reduces objects to a skeleton-like representation, preserving their structure.
Boundary Extraction: Erode or Dilate - Orig

Shape Descriptor: diff for different shapes
Shape Features: either boundary or region
Distance/Area-ConvexArea/Perimeter/
Compactness = (4.pi.area / (perimeter*2)) - **Solidity**=(area/convex area)
Convexity = (convex perimeter / perimeter) - **Roundness** = (4.pi.area)/(convex permiterer*2) - Eccentricity/Calliper Dimensions.
circular variance: how similar is the object to the circle MSE calculated. Sth like compactness.
Direction: elongated axis is directed to some angle.

Topological Descriptors: useful for global description of objects (features that do not change with elastic deformation. Number of connected components. **Euler number =** num of component - num of holes

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PNG: Lossless compression, meaning no quality loss. Great for images with text, graphics, and transparency.
JPEG: Lossy compression, meaning some quality is lost. Ideal for photos and images with many colors.
Data Compression Concepts: 1- Dictionary Encoding (GIF + PNG). 2- FrequencyDomain(JPEG)

Dictionary encoding is a lossless data compression technique that replaces repeated sequences with shorter, unique codes.1-**Dictionary Creation**: A table is created to map original sequences to shorter codes. 2-**Encoding**: When a sequence is encountered, it is replaced with its corresponding code from the dictionary.3-**Decoding**: reversed

Entropy Encoding For most likely char , we want a short code.
Encoded data stream: E[p(code) × Length(code)] × N_symbols

PNG / GIF compression: Colour Quantization (GIF, PNG)| RGB colour (PNG) => Dictionary + Entropy Encoding (LZ77, LZW)
JPEG Compression: Frequency-Space Conversion => Quantization +EntropyEncoding.
- Color space transformation. RGB=>Y',CB,CR
- Y (greyscale intensity): Not downsampled
- CB, CR (blue, red colour): downsample by 2
- **Discrete cosine transform**: JPEG divides the image into 8×8 blocks and applies the DCT to convert pixel values into frequency components.
- **Quantization**: Frequency components are quantized, reducing less important frequencies more aggressively.

Lossy Compression: JPEG is a lossy compression method, meaning some data is discarded to reduce file size.
Quantization Artifacts: At higher compression levels (lower quality), the quantization step becomes more aggressive, leading to visible artifacts. These artifacts often appear as blocky patterns because the 8×8 blocks are processed independently.
8×8 is small enough to be processed quickly and large enough to capture significant image details. It also aligns well with the Discrete Cosine Transform (DCT)

Spatial transforms: maps points from one image to corresponding points in another image.
Rigid: rotations and translations **Affine**: skew and scaling **Deformations**: Orthogonal to a plane free-form mapping
Optimizer: Gradient ascent. computes the "next best guess" in two steps: Estimate the gradient of the objective function at the current point. Take a step in the solution space in the direction of greatest positive gradient. X' = X + $\ddot{\nabla} F(x)$ | $x^{k+1} = x^k + \alpha \ddot{\nabla} S(x)$

S(x,y,θ) (in 3D) $\nabla S(\mathbf{x}) = \left[\frac{\partial}{\partial \mathbf{x}}\mathbf{S}(\mathbf{x},\mathbf{y},\theta), \frac{\partial}{\partial \mathbf{y}}\mathbf{S}(\mathbf{x},\mathbf{y},\theta), \frac{\partial}{\partial \theta}\mathbf{S}(\mathbf{x},\mathbf{y},\theta)\right]$

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1 Geometric transformations. 2 Intensity transformations: we might not "land" on a single pixel location. Some techniques estimate the parameters of the "backwards" transformation. Problem if the mapping function is non-invertible.

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} s_{xx} & s_{xy} & t_x \\ s_{yx} & s_{yy} & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

(Translation, Scaling, Rotation, and Shearing)

Translate	Scale	Rotate	Shear
$\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} c & s & 0 \\ -s & c & 0 \\ 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 1 & 0.5 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}$
x+1 y+1	2x 2y	cx+sy -sx + cy	x+1/2y y

Spatial transformation
Rigid: are geometric transformations that preserve the shape and size of an object: Translation, Rotation, Reflection.
Affine: no more preservation of length and **angle**. Translation Rotation Reflection Scaling Shearing.Rigid, Affine, Projective, Perspective, Global Polynomial, Spline).

SIFT (Scale invariant feature transform) Invariants to:Scale, Rotation, Illumination, Viewpoint. ***1-Construct a scale space***: make some blurred version of image, and then resize all versions in half. ***2-Calculate LoG*** *(Laplacian of Gaussian) Approximation* ***3-Find key points*** Locate maxima/minima in LoG images. (Approximate" because the maxima/minima almost never lies exactly on a pixel.) ***4-Get rid of bad key points (a technique similar to the Harris Corner Detector)*** *4-1*-Removing low contrast features: If the intensity at the current pixel in the DoG image (that is being checked for minima/maxima) is less than a certain value, it is rejected. *4-2-Removing edges:* Reject points with strong edge response in one direction only. **5-Assign an orientation to the keypoints Generate SIFT features.**
Application: Pulmonary CT images acquired at breath hold (a) maximum exhale and (b) maximum inhale. 2- Image Registration: Aligning medical images from different modalities (e.g., MRI and CT scans) for accurate comparison and analysis.

Registration algorithms: *Rigid & affine:* 1-Landmark based 2-Edge based. *Non-rigid:* using basis functions, using splines.
Registration algorithms (Similarity measures): Statistical • Sum of Squared Differences (SSD) NSSD • Cross Correlation (C;C) • NCC
Limitations of statistical similarity measures: Well suited for monomodal registration (not multimodal) -> alternative ->
Information theory-based: maximize the amount of shared information in two images. Algorithms used:
1- **Joint entropy:** Joint entropy measures the amount of information in the two images combined (t**he less bette**r)2- **Mutual information:** A measure of how well one image explains the other, and is maximized at the optimal alignment.

Joint entropy: Low entropy, order - High entropy, disorder. Information is Entropy.
- Joint Histogram img X and Y. Num of occurrence where X(i)=Y(j)
- A joint histogram is a useful tool for visualizing the relationship between the intensities of corresponding voxels in two or more images.
- Joint entropy, measure of dispersion, low value -> high alignment
- Joint entropy as a similarity measure, suited for multimodal
- **Problem:** complete misregistration with few overlap can lead to low joint entropy.

Why does registration seem so complicated? finding accurate correspondences between features can be challenging
Why would we be interested in multi-image registration? To create a more comprehensive 3D model of a structure. To analyze changes over time or across different conditions.
Joint entropy: global approach based on mutual info/statistical dependance. Works well with multimodal images CT to MRI. Robust to noise. **Useful When**: Images lack distinct features or have significant differences in appearance (multimodal).Best for situ where texture and pattern and global intensity vary between images. Computationally expensive for large or high-res images. If images contain less overlapping info, perform poorly. Global and non-linear
SIFT: local feature based. Effective under change in scale rota and illumination. Can align images with significant distortion or local diff. **Useful When**: There are distinct and repeatable features in the images, such as corners, edges, or textures. Best for monomodal image registration (same intensity dist). Situation with well defined high-contrast features. Works with partial overlaps. Poorly on multimodal images with intensity or texture differ signific. Local and affine.

Image Reconstruction
Backprojection: We have unknown FT. We perform projection in many different angles. Then we can have information from our FT. Then we take inverse FT, then we get a reconstructed image.
After projecting at all angles, we need **filtering** to enhance them. **Oversampling** at low freqs (collect more data for these areas than necessary), **undersampling** at high freqs (edge small texture) we don't capture enough details, may lead to blurring.

RAM-lak filter does not work well with noisy data since it is a high pass filter. High-frequency, can amplify noise present.

Projection Data: raw data collected from different angles during a scan, which is then used to reconstruct cross-sectional images. It's crucial in medical imaging because it provides the necessary information to create detailed images of the body's internal structures
Blurred Backprojected Image: because the simple backprojection method oversamples the center and undersamples the edges.

Shepp-Logan Filter: The Shepp-Logan filter is designed to reduce the noise sensitivity of the Ram-Lak filter by applying a sinc function, which smooths the high-frequency components and reduces artifacts

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Discuss and compare strategies for these textures:
O Statistical Approach: **Gray-Level Co-occurrence Matrix (GLCM)**: This method analyzes the spatial relationship between pixels by creating a matrix that considers the frequency of pixel pairs with specific values and spatial relationships. It's useful for identifying texture patterns and is widely used in medical imaging for tumor detection and tissue classification. **(GLR)**: This approach measures the length of consecutive pixels with the same gray level in a specific direction. It's effective for identifying textures with repetitive patterns and is often used in medical imaging to analyze tissue structures**Spectral Approach**:**Law's Texture Energy (LTE)**: This method uses convolution masks to highlight different texture features like edges, spots, and waves. It's beneficial for enhancing texture details and is applied in medical imaging to improve the visibility of fine structures. **Fourier Transform (FT)**: T transforms the image from the spatial domain to the frequency domain, allowing the analysis of periodic patterns and textures. It's useful in medical imaging for detecting and analyzing repetitive structures and pattern.
Discuss why skeletonization is useful:
Skeletonization reduces a shape to its essential structure, making it easier to analyze and process. It's useful in pattern recognition, image analysis, and computer vision because it simplifies complex shapes while preserving their topology. For example, in vascular imaging, skeletonization helps in identifying and analyzing the branching patterns of blood vessels, which is crucial for diagnosing vascular diseases
Compare two shape parameters and why some would be more or less useful for this problem:
Shape parameters like area, perimeter, compactness, and eccentricity can be compared. For instance, compactness ($perimeter^2$/area) is useful for distinguishing between shapes with similar areas but different perimeters. Eccentricity (ratio of the major axis to the minor axis) helps in identifying elongated shapes. The usefulness depends on the specific problem and the characteristics of the shapes being analyzed.
Calculate pixel probabilities. Explain how entropy encoding can compress:
Pixel probabilities refer to the likelihood of each pixel value occurring in an image. Entropy encoding compresses data by assigning shorter codes to more frequent pixel values and longer codes to less frequent ones, reducing the overall size of the data
What errors if you separate classes with x>y?:
Separating classes with x>y might lead to misclassification if the classes are not linearly separable or if the decision boundary is not appropriate for the data distribution
What weights on perceptron to implement x>y?:
To implement x>y in a perceptron, you would set the weights such that the decision boundary is a line where x=y. For example, weights could be [1, -1] with a bias of 0.
Why are gradients so important in IP algorithms?:
Gradients are crucial in image processing algorithms because they provide information about the rate of change in pixel values, which is essential for edge detection, image enhancement, and other tasks.
Why are ways to speed up gradients valuable?:
Speeding up gradient calculations is valuable because it reduces the computational time and resources required for training models and processing images, making algorithms more efficient and scalable.
What is overfitting in ML?: Overfitting occurs when a machine learning model learns the training data too well, including noise and outliers, resulting in poor generalization to new, unseen data.
What is bias in ML?: Bias in machine learning refers to the error introduced by approximating a real-world problem, which may be complex, by a simplified model. High bias can lead to underfitting, where the model is too simple to capture the underlying patterns in the data.