Image Segmentation

Detection of Discontinuities

Edge linking and boundary detection

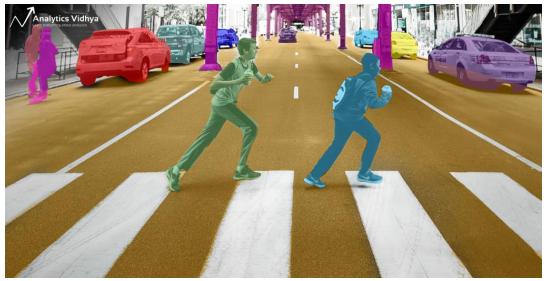
Thresholding

Region Based

Segmentation

Image Segmentation

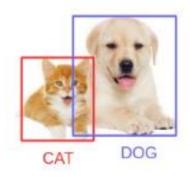
- Image segmentation is a fundamental task in image processing that partitions an image into meaningful segments or regions based on certain criteria.
- ➤ This process is essential for object recognition, analysis, and understanding in computer vision applications.



- ➤ By breaking down an image's complex visual information into uniquely shaped segments, this technique facilitates quicker and more sophisticated image processing
- ➤ Here's a breakdown of what image segmentation is and what it does:
 - o **Goal:** Simplify and analyze images by separating them into different segments. This makes it easier for computers to understand the content of the image.
 - o **Process:** Assigns a label to each pixel in the image. Pixels with the same label share certain properties, like color or brightness.
 - o Benefits:
 - Enables object detection and recognition in images.
 - Allows for more detailed analysis of specific image regions.



Image Localization

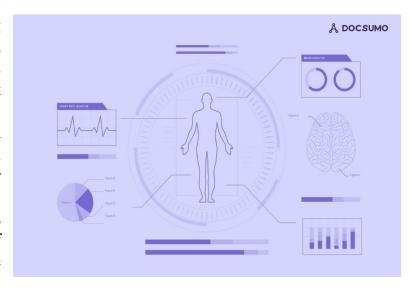


Object Detection

Applications

1. Medical Imaging:

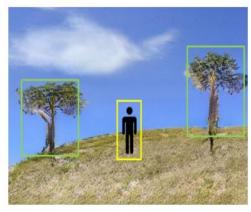
- Application: Segmenting organs, tissues, tumors, and anomalies in MRI, CT scans for diagnosis and treatment planning.
- Example: Identifying and measuring tumor growth in medical images to monitor disease progression.
- Advantages: Enables precise localization of abnormalities for accurate diagnosis.



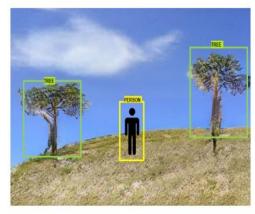
 Disadvantages: Sensitivity to noise and variations in image quality can affect segmentation accuracy.

2. Object Detection and Recognition:

- **Application:** Identifying objects in scenes for autonomous driving, robotics, and surveillance.
- Example: Segmenting pedestrians, vehicles, and traffic signs in real-time video streams for autonomous vehicles.
- Advantages: Enables robust object detection and tracking in complex environments.
- Disadvantages: Challenges include occlusions, varying lighting conditions, and complex object shapes.



(1) Object Detection



(2) Object Recognition

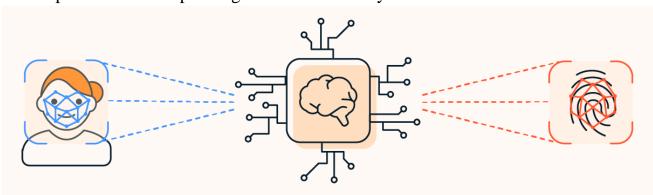
3. Satellite and Aerial Imagery:

- Application: Land cover classification, urban planning, and environmental monitoring.
- **Example:** Segmenting different land types (e.g., vegetation, water bodies, urban areas) in satellite images.
- Advantages: Facilitates accurate mapping and monitoring of land use changes over time.
- o **Disadvantages:** Large-scale imagery processing requires efficient algorithms to handle computational complexity.



4. Biometrics and Security:

- **Application:** Face recognition, fingerprint analysis, and iris segmentation for biometric identification.
- **Example:** Segmenting facial features to extract unique identifiers for biometric authentication systems.
- Advantages: Enhances security measures by accurately identifying individuals based on unique biometric characteristics.
- o **Disadvantages:** Sensitivity to variations in pose, illumination, and facial expressions can impact segmentation accuracy.



- Let's understand the image **segmentation** algorithm using a simple example. Consider the below image:
- ➤ There's only one object here a dog. We can build a straightforward cat-dog classifier model and predict that there's a dog in the given image. But what if we have a cat and a dog in a single image?

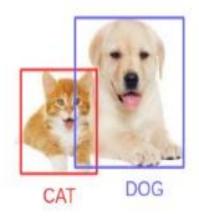


- We can train a multi-label classifier, for instance. However, there's another caveat—we won't know the location of either animal or object in the image.
- ➤ That's where image localization comes into the picture (no pun intended!). It helps us identify a single object's location in the given image. We rely on object detection (OD) if we have multiple objects present. We can predict the location and class for each object using OD.





Image Localization



Object Detection

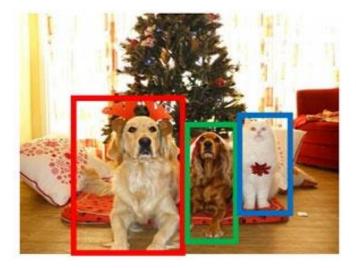
➤ Before detecting the objects and even before classifying the image, we need to understand what it consists of. Enter Image Segmentation.

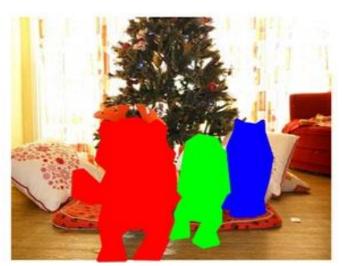
How Does Image Segmentation Work?

- ➤ We can divide or partition the image into various parts called segments.
- ➤ It's not a great idea to process the entire image at the same time, as there will be regions in the image that do not contain any information.
- ➤ By dividing the image into segments, we can use the important segments to process the image. That, in a nutshell, is how image segmentation works.
- ➤ An image is a collection or set of different pixels.
- ➤ We group the pixels that have similar attributes using image segmentation. Take a moment to go through the below visual (it'll give you a practical idea of segmentation in image processing):

Object Detection

Instance Segmentation



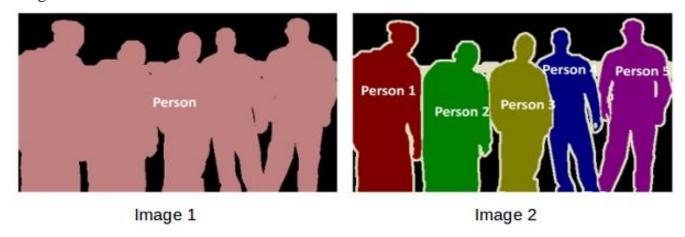


Description builds a bounding box corresponding to each class in the image. But it tells us nothing about the object's shape—we only get the set of bounding box coordinates. We want more information—this is too vague for our purposes.

The <u>image segmentation algorithm</u> creates a pixel-wise mask for each object in the image. This technique gives us a far more granular understanding of the object(s) in the image.

Different Types of Image Segmentation

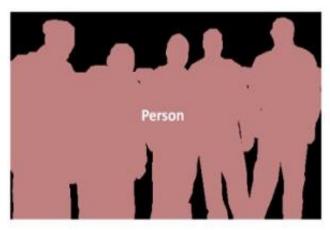
We can broadly divide image segmentation techniques into two types. Consider the below images:

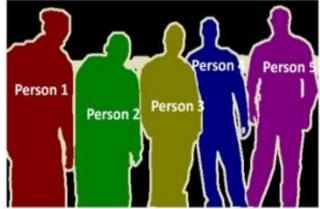


Can you identify the difference between these two? Both images use image segmentation techniques to identify and locate the people present.

- In image 1, every pixel belongs to a particular class (either background or person).

 Also, all the pixels belonging to a particular class are represented by the same color (background as black and person as pink). This is an example of semantic segmentation
- Image 2 also assigns a particular class to each pixel of the image. However, different objects of the same class have different colors (Person 1 as red, Person 2 as green, background as black, etc.). This is an example of instance segmentation





Semantic Segmentation

Instance Segmentation

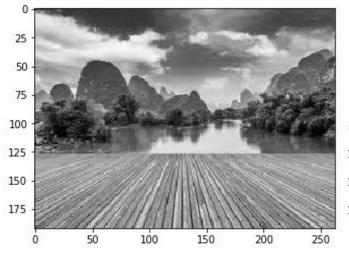
Let me quickly summarize what we've learned. If there are 5 people in an image, semantic segmentation will focus on classifying all the people as a single instance. Instance segmentation, however, will identify each of these people individually.

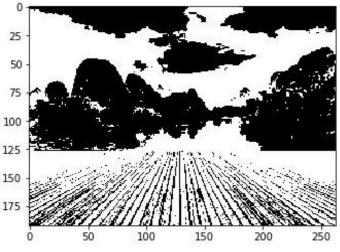
Region-based Segmentation

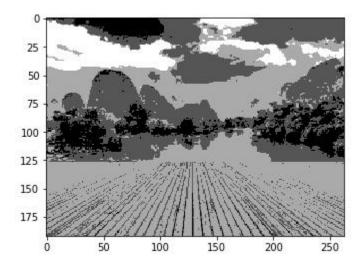
- ➤ One simple way to segment different objects could be to use their pixel values. An important point to note the pixel values will be different for the objects and the image's background if there's a sharp contrast between them.
- In this case, we can set a threshold value. The pixel values falling below or above that threshold can be classified accordingly (as objects or backgrounds). This technique is known as Threshold Segmentation.



➤ If we have multiple objects along with the background, we must define multiple thresholds. These thresholds are collectively known as the local threshold.







There are four different segments in the above image. You can set different threshold values and check how the segments are made.

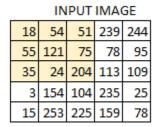
- > Some of the advantages of this method are:
 - Calculations are simpler
 - > Fast operation speed
 - ➤ When the object and background have high contrast, this method performs well

However, this approach has some limitations. When there is no significant grayscale difference or an overlap of the grayscale pixel values, it becomes very difficult to get accurate segments.

Edge Detection Segmentation

- ➤ What divides two objects in an image? An edge is always between two adjacent regions with different grayscale values (pixel values). The edges can be considered as the discontinuous local features of an image.
- ➤ We can use this discontinuity to detect edges and hence define a boundary of the object. This helps us detect the shapes of multiple objects in a given image. Now, the question is, how can we detect these edges? This is where we can make use of filters and convolutions.

> The below visual will help you understand how a filter convolves over an image :



WEIGHT				
1	0	1		
0	1	0		
1	0	1		



	IN	PUT	IMA	GE
18	54	51	239	244
55	121	75	78	95
35	24	204	113	109
3	154	104	235	25
15	253	225	159	78



429 686

		IN	PUT	IMA	GE
1	8	54	51	239	244
5	5	121	75	78	95
3.	5	24	204	113	109
13	3	154	104	235	25
1	5	253	225	159	78





	IN	IPUT	IMA	GE
18	54	51	239	244
55	121	75	78	95
35	24	204	113	109
3	154	104	235	25
15	253	225	159	78

36	WEIGHT				
ſ	1	0	1		
	0	1	0		
	1	0	1		

429 686 633 412

- ➤ Here's the step-by-step process of how this works:
 - o Take the weight matrix
 - o Put it on top of the image
 - o Perform element-wise multiplication and get the output
 - o Move the weight matrix as per the stride chosen
 - o Convolve until all the pixels of the input are used

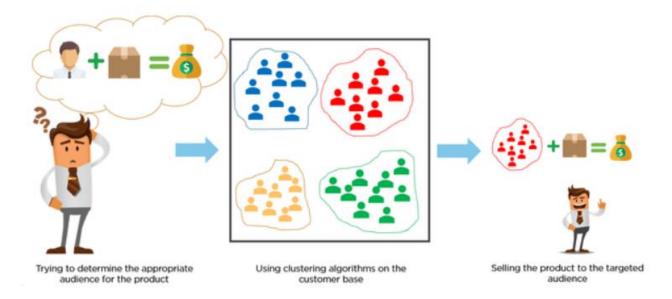
The values of the weight matrix define the output of the convolution. My advice: It helps to extract features from the input.

Researchers have found that choosing some specific values for these weight matrices helps us detect horizontal or vertical edges (or even the combination of horizontal and vertical edges).

One such weight matrix is the Sobel operator. It is typically used to detect edges. The Sobel operator has two weight matrices—one for detecting horizontal edges and the other for detecting vertical edges.

Clustering-based Image Segmentation

This idea might have come to you while reading about image segmentation techniques. Can't we use clustering techniques to divide images into segments? We certainly can!



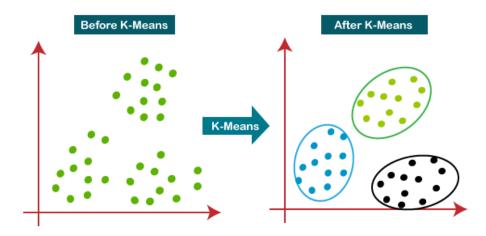
In this section, we'll get an intuition of clustering (it's always good to revise certain concepts!) and how to use it to segment images.

Clustering is dividing the population (data points) into many groups, such that data points in the same groups are more similar to other data points in that group than those in other groups. These groups are known as clusters.

K-means Clustering

One of the most commonly used clustering algorithms is <u>k-means</u>. Here, the k represents the number of clusters (not to be confused with k-nearest neighbor). Let's understand how k-means works:

- 1. First, randomly select k initial clusters
- 2. Randomly assign each data point to any one of the k clusters
- 3. Calculate the centers of these clusters
- 4. Calculate the distance of all the points from the center of each cluster
- 5. Depending on this distance, the points are reassigned to the nearest cluster
- 6. Calculate the center of the newly formed clusters
- 7. Finally, repeat steps (4), (5) and (6) until either the center of the clusters does not change or we reach the set number of iterations



The key advantage of using the <u>k-means algorithm</u> is that it is simple and easy to understand. We are assigning the points to the clusters closest to them.

Detection of Discontinuities

1. Edge Detection:

- o **Definition:** Identifies points in an image where brightness changes sharply.
- Methods: Gradient-based (Sobel, Prewitt, Roberts), Laplacian-based, Canny edge detector.
- o **Purpose:** Locates boundaries of objects in an image.

2. Line Detection:

- o **Definition:** Identifies straight lines or curves in an image.
- **Methods:** Hough transform.
- o **Purpose:** Useful for detecting shapes or patterns characterized by linear features.

Edge Linking and Boundary Detection

1. Edge Linking:

- o **Definition:** Connects edge segments to form continuous contours or boundaries.
- o **Methods:** Region growing, edge following, chain coding.
- o **Purpose:** Produces complete object boundaries for further analysis.

2. Boundary Detection:

- o **Definition:** Accurately traces the outline of an object or region.
- o **Methods:** Gradient-based boundary following, active contours (snakes).
- **Purpose:** Provides precise segmentation of objects from the background.

Thresholding

1. Global Thresholding:

- o **Definition:** Divides an image into foreground and background based on a fixed threshold value.
- **Methods:** Simple thresholding, adaptive thresholding.
- Purpose: Segments objects with distinct intensity differences from the background.

2. Local Thresholding:

- o **Definition:** Applies different thresholds to different parts of an image.
- Methods: Otsu's method, adaptive thresholding.
- **Purpose:** Handles images with varying illumination and noise levels.

Region-Based Segmentation

1. Region Growing:

- Definition: Starts from seed points and merges neighboring pixels or regions based on similarity criteria.
- o **Methods:** Region merging, split and merge.
- o **Purpose:** Groups pixels into coherent regions sharing similar properties.

2. **Region Splitting:**

- Definition: Divides an image into smaller, homogeneous regions based on predefined criteria.
- o **Methods:** Watershed segmentation, graph-based segmentation.
- Purpose: Segments objects with complex shapes or overlapping structures