**REGULAR QUESTIONS – 1**

**Object Detection Questions**

1. What is the purpose of anchor boxes in object detection, and how are they generated?

2. Explain how the Intersection over Union (IoU) metric is used to evaluate object detection models.

3. What are some common challenges when detecting small objects in images?

4. How does the Faster R-CNN model differ from a traditional CNN used for image classification?

5. Describe how you would fine-tune a pre-trained object detection model on a new dataset.

**Object Detection Questions**

**1. Purpose of Anchor Boxes in Object Detection and How They Are Generated:**  
Anchor boxes are predefined bounding boxes of various sizes and aspect ratios used to detect objects of different shapes and scales in an image. During training, the model matches these anchor boxes with ground-truth boxes and adjusts their dimensions and positions.

* **Generation:** Anchor boxes are created at each feature map location (e.g., sliding window approach) and are parameterized by scales and aspect ratios. Multiple anchors are assigned to each feature map location to capture objects of varying sizes.

**2. Intersection over Union (IoU) Metric for Evaluating Object Detection Models:**  
IoU measures the overlap between the predicted bounding box and the ground truth box.

**Usage:**

* IoU > 0.5 is typically considered a correct detection.
* IoU thresholds (e.g., 0.5 or 0.75) are used to calculate precision and recall.
* It is a key metric for calculating Mean Average Precision (mAP).

**3. Common Challenges When Detecting Small Objects in Images:**

* **Low Resolution:** Small objects may occupy very few pixels, leading to insufficient features for detection.
* **Occlusion:** Small objects are often obscured by other objects.
* **Context Dependency:** Small objects are harder to detect without context (e.g., a small car in a large road scene).
* **Anchor Box Design:** Improper scaling of anchor boxes can fail to match small objects.

**Solutions:** Using FPN, context-aware features, higher-resolution inputs, and specialized loss functions like focal loss.

**4. Faster R-CNN vs. Traditional CNN for Image Classification:**

* **Faster R-CNN:**
  + Performs both object detection (localizing bounding boxes) and classification.
  + Includes a Region Proposal Network (RPN) for generating candidate object regions.
  + Uses multi-scale feature maps (e.g., FPN) to detect objects of varying sizes.
* **Traditional CNN:**
  + Only classifies the entire image into a single category.
  + Lacks the capability to localize objects within the image.

**5. Fine-Tuning a Pre-Trained Object Detection Model on a New Dataset:**

1. **Load a Pre-Trained Model:** Use a model trained on a similar dataset (e.g., COCO or Pascal VOC).
2. **Replace the Detection Head:** Modify the final layers to match the number of classes in the new dataset.
3. **Freeze Layers:** Freeze early layers (e.g., backbone) and fine-tune higher layers.
4. **Train with Augmentation:** Apply data augmentation to adapt to new scenarios.
5. **Set a Lower Learning Rate:** Use a smaller learning rate for fine-tuning pre-trained weights.
6. **Evaluate and Iterate:** Use metrics like mAP and IoU to refine the model.