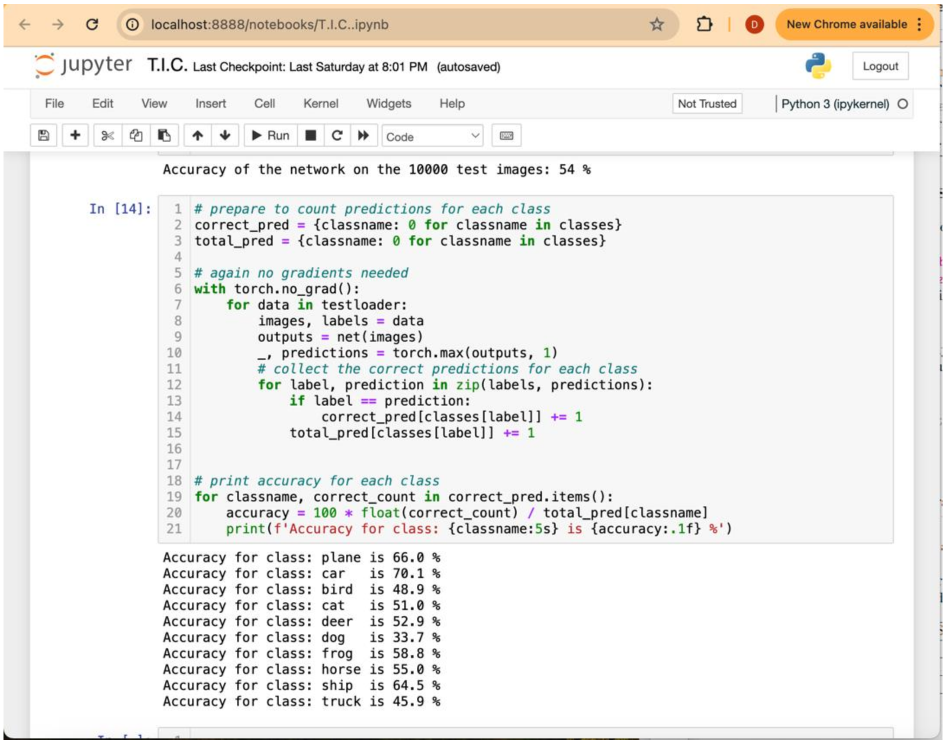
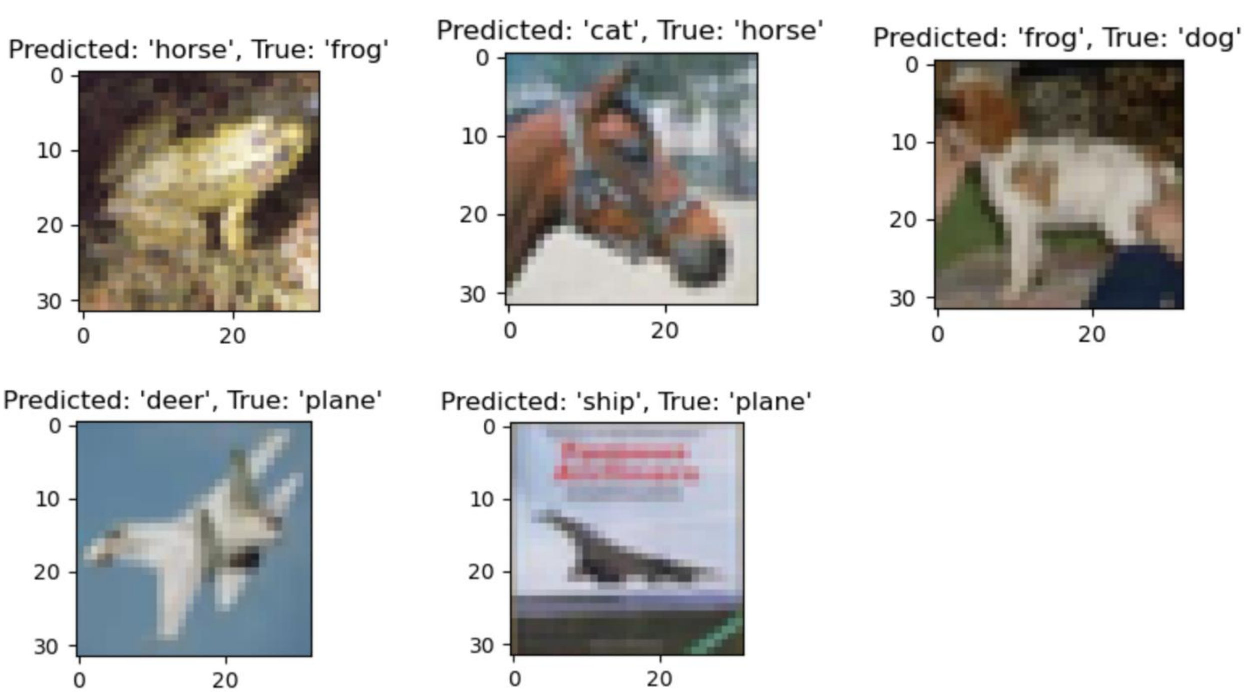
TRAINING AN IMAGE CLASSIFIER

Task 1 Results Reproduction snapshot:



Task 2 Failure Cases:



Task 3 Hyperparameter Tuning:

Epochs	Batch Size	Learning Rate	Momentum	Test Accuracy

2	4	0.001	0.9	54%
4	4	0.001	0.9	58%
2	8	0.001	0.9	51%
2	4	0.0005	0.9	51%
2	4	0.001	0.45	43%
4	8	0.0005	0.45	38%
4	***4***	***0.001***	***0.9***	***58%***

Task 4 Dataset augmentation:

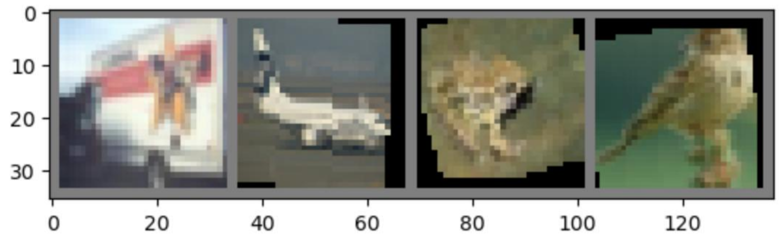
So, what I did was initially ran the model to replicate the accuracy from the tutorial. Then ran it again using the transformed dataset to see what happened. But I also did one where it was only ran using the augmented set.

a. There where 3 types of augmentations applied: Horizontal flips, Rotations, Translations. They were all random. The flips were applied randomly with a fixed probability of 50%. The rotations were applied with a random degree between -20 and 20 degrees. The translations can be up to 10% of the image's width to the left/right or up/down.
b. The performance did not improve when running the model on the augmented set after running it on regular set first. Performance dropped from 54% accuracy to 52% accuracy. Running the model only on the augmented set gives a performance of 46%. However, this was with the hyperparameters tuned to what the tutorial had them as. When I increased the epoch from 2 to 8, and run the model once on the augmented dataset, I get an accuracy of 56%. So not much of an increase from the original, but an increase, nonetheless.
c. Data augmentation helped improve accuracy b/c the transformations diversified the training examples. The model now has more orientations/perspectives to learn from which will help with future predictions when testing.
d. I think brightness/dimness and scaling transformations can be of good use. The scaling transformations would help b/c images are not always taken from an ideal distance away, it can be taken from very up close or very far away. Similarly, the lighting for pictures isn't always ideal, so presenting the model with different variations of these transformations will deepen it's learning and increase accuracy.

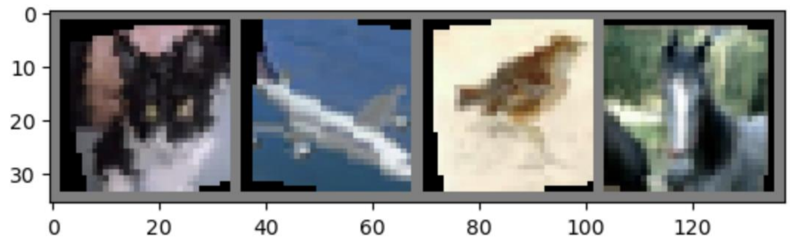
Code to augment:

```
transform_augmented = transforms.Compose([
    transforms.RandomHorizontalFlip(),  # Flip the image randomly with a given probability
    transforms.RandomRotation(20),  # Random rotation between -20 and 20 degrees
    transforms.RandomAffine(degrees=0, translate=(0.1, 0.1)),  # Random translation
    transforms.ToTensor(),  # Convert images to tensors
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))  # Normalize images
])
```

Output of augmentations:




```
truck plane frog  bird
```




```
cat   plane bird  horse
```

Task 5 (Extra Credit):

1. The classifier's prediction would be completely wrong. I ran some code and the ground truth output was this, then when I ran the code to get the prediction, it read "dog dog bird dog"
   Code:

```
#MNIST STUFF

from torchvision import datasets, transforms
from torch.utils.data import DataLoader

transform_mnist = transforms.Compose([
    transforms.Grayscale(3),  # Convert MNIST images to 3-channel
    transforms.Resize((32, 32)),
    transforms.ToTensor()
])

mnist_test = datasets.MNIST(root='./data', train=False, download=True,
transform=transform_mnist)
mnist_loader = DataLoader(mnist_test, batch_size=64, shuffle=False)

dataiter = iter(mnist_loader)
images, labels = next(dataiter)

# print images
imshow(torchvision.utils.make_grid(images))
print('GroundTruth: ', ' '.join(f'{classes[labels[j]]:5s}' for j in range(4)))
```

Output:

```
GroundTruth:  horse bird  car   plane
```

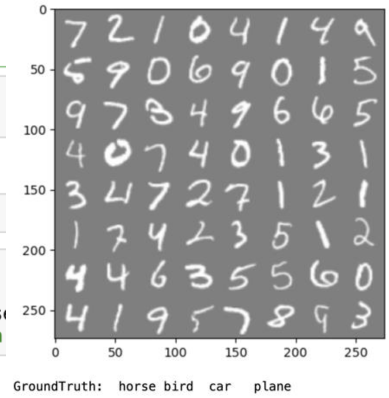
```
net = Net()
net.load_state_dict(torch.load(PATH))
```

```
<All keys matched successfully>
```

```
outputs = net(images)
```

```
_, predicted = torch.max(outputs, 1)

print('Predicted: ', ' '.join(f'{classe
                              for j in
```

```
Predicted:  dog   dog   bird  dog
```



2. Well for seen classes the model would give high confidence because image features would resemble features in the training data. Whereas for unseen classes the confidence would vary unpredictably because the image features may have patterns the model thinks it recognizes where other patterns it doesn't.
3. Well, some kind of unseen class detection could be implemented using some SoftMax threshold that will flag or refuse the image, almost like how a bouncer checks IDs before letting people into a club. Similarly, the CNN would check against the threshold before giving any predictions.

EVALUATION OF OBJECT DETECTION MODELS

Task 1: *Load Object Detector Models*

Code:

```
# Download a pretrained model
model0 = torchvision.models.detection.fasterrcnn_resnet50_fpn(pretrained=True)

# maskrcnn_resnet50_fpn
model1 = torchvision.models.detection.maskrcnn_resnet50_fpn(pretrained=True)

# retinanet_resnet50_fpn
model2 = torchvision.models.detection.retinanet_resnet50_fpn(pretrained=True)

# ssdlite320_mobilenet_v3_large
model3 = torchvision.models.detection.ssdlite320_mobilenet_v3_large(pretrained=True)

# Inference
model0.eval()
model1.eval()
model2.eval()
model3.eval()
```

Task 2: *Object Detection Pipeline*

Code:

```
def get_detection(img, model, threshold=0.5):
    pred = model([img]) # Pass the image to the model

    # pred is a list and each element of that list is a dictionary with keys:
"labels", "scores", and "boxes"
```

```
    pred_classes = [COCO_INSTANCE_CATEGORY_NAMES[i] for i in
list(pred[0]['labels'].numpy())] # Get the Prediction Classes

    # !!!! Complete the following (edited the next 3 lines)
    pred_boxes =  pred[0]['boxes'].detach().numpy()  # Get the Prediction Boxes
    pred_scores =  pred[0]['scores'].detach().numpy()  # Get the Prediction Scores

    high_score_indices = [i for i, score in enumerate(pred_scores) if score >
threshold]
    if high_score_indices:
        last_index = high_score_indices[-1] + 1
        pred_boxes = pred_boxes[:last_index]
        pred_classes = pred_classes[:last_index]
    else:
        pred_boxes = np.array([])  # In case no scores are above threshold
        pred_classes = []

    return pred_boxes, pred_classes
```

Task 3: *Display Detections*

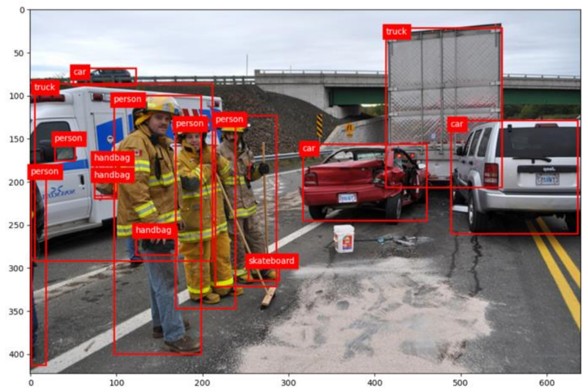
Code:

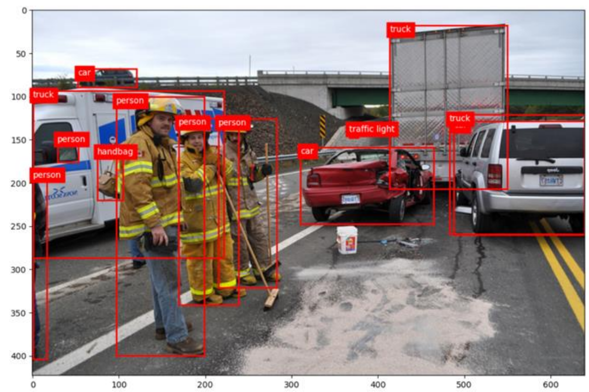
```
def show_detections(img_path, model, threshold=0.5):
    img = Image.open(img_path) # Load the image
    img = transform(img) # Apply the transform to the image
    boxes, pred_cls = get_detection(img, model, threshold) # Get predictions
    img = cv2.imread(img_path) # Read image with cv2
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB) # Convert to RGB
    # !!!! Complete the following
    # write code to display the image, overlay the bounding boxes and predicted
classes on top of the image
    fig, ax = plt.subplots(figsize=(12, 8))  # Set up the figure and axes
    ax.imshow(img)
    # !!!!
    for box, cls in zip(boxes, pred_cls):
        x, y, xmax, ymax = box
        width = xmax - x
        height = ymax - y
        # Draw a rectangle around each box
        rect = patches.Rectangle((x, y), xmax - x, ymax - y, linewidth=2,
edgecolor='red', facecolor='none')
        ax.add_patch(rect)
        # Add label
        ax.text(x, y, cls, verticalalignment='top', color='white', fontsize=10,
backgroundcolor='red')
    plt.show()


!wget https://www.tejasgokhale.com/images/vehicle.png -O vehicle.jpg
# code to use show_detections to display results for `model0,model1,model2,model3`
# !!!! Complete this
```

```python
img_path = 'vehicle.jpg'

show_detections(img_path, model0, threshold=0.5)
show_detections(img_path, model1, threshold=0.5)
show_detections(img_path, model2, threshold=0.5)
show_detections(img_path, model3, threshold=0.5)
```

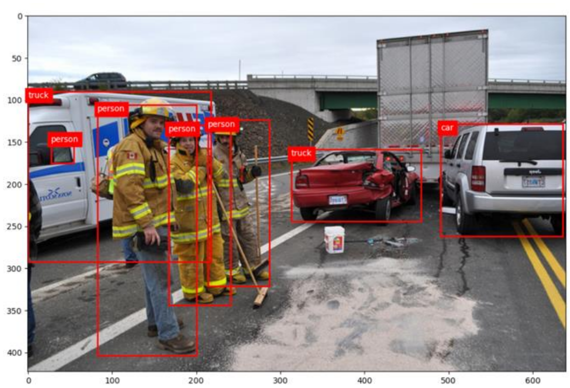
<u>Output:</u>

Model0 || Model1:





Model2 || Model3:



Task 4: *Evaluation using MS-COCO dataset.*

Calculate meanIOU over entire dataset of 100 images and report meanIOU for all 4 models in a table:
Code:

```python
coco_annotations_file="/Users/fneba/Desktop/691_Computer_Vision/hw4/coco_ann2017/annotations/instances_val2017.json"
coco_images_dir="/Users/fneba/Desktop/691_Computer_Vision/hw4/coco_val2017/val2017"
coco= COCOParser(coco_annotations_file, coco_images_dir)

img_ids = coco.get_imgIds()
img_ids = img_ids[:100]

# For mean IoU calculation
mean_ious0 = [] # added for model0
mean_ious1 = [] # added for model1
mean_ious2 = [] # added for model2
mean_ious3 = [] # added for model3

for i, im in enumerate(img_ids):
```

```
    image = Image.open(f"{coco_images_dir}/{str(im).zfill(12)}.jpg")
    image = transform(image)
    pred_boxes0, pred_class0 = get_detection(image, model0)
    pred_boxes1, pred_class1 = get_detection(image, model1)
    pred_boxes2, pred_class2 = get_detection(image, model2)
    pred_boxes3, pred_class3 = get_detection(image, model3)

    ann_ids = coco.get_annIds(im)
    annotations = coco.load_anns(ann_ids)
    # Calculate IoU for each model
    mean_ious0.append(eval_iou(pred_boxes0, pred_class0, annotations))
    mean_ious1.append(eval_iou(pred_boxes1, pred_class1, annotations))
    mean_ious2.append(eval_iou(pred_boxes2, pred_class2, annotations))
    mean_ious3.append(eval_iou(pred_boxes3, pred_class3, annotations))


print(f"Mean IoU for model0 over 100 images: {np.mean(mean_ious0)}")
print(f"Mean IoU for model1 over 100 images: {np.mean(mean_ious1)}")
print(f"Mean IoU for model2 over 100 images: {np.mean(mean_ious2)}")
print(f"Mean IoU for model3 over 100 images: {np.mean(mean_ious3)}")
```

Output:

Model	meanIOU
model0	0.5766270008358215
model1	0.5795787956734314
model2	0.6217368327239078
model3	0.6054661987556592

Similarly, report the precision and recall of each model:
Code:

```
def calculate_matches(pred_boxes, pred_classes, annotations, iou_threshold=0.5):
    TP = 0
    FP = 0
    FN = 0

    matched_gt_indices = set()  # Keep track of matched ground truth indices

    # Check each prediction for potential matches
    for pred_box, pred_class in zip(pred_boxes, pred_classes):
        found_match = False
        for idx, ann in enumerate(annotations):
            gt_bbox = [ann['bbox'][0], ann['bbox'][1], ann['bbox'][0] +
ann['bbox'][2], ann['bbox'][1] + ann['bbox'][3]]
            gt_class_id = ann["category_id"]
            pred_class_id = COCO_INSTANCE_CATEGORY_NAMES.index(pred_class) if
pred_class in COCO_INSTANCE_CATEGORY_NAMES else -1

            if pred_class_id == gt_class_id and iou(pred_box, gt_bbox) >=
iou_threshold:
                if idx not in matched_gt_indices:
```

```
                matched_gt_indices.add(idx)
                found_match = True
                TP += 1
                break

        if not found_match:
            FP += 1

    # Compute FN as ground truths that were not matched
    FN = len(annotations) - len(matched_gt_indices)

    return TP, FP, FN


models = [model0, model1, model2, model3]

TPs = [0, 0, 0, 0]  # TP for model0, model1, model2, model3
FPs = [0, 0, 0, 0]  # FP for model0, model1, model2, model3
FNs = [0, 0, 0, 0]  # FN for model0, model1, model2, model3

for im in img_ids:
    image_path = f"{coco_images_dir}/{str(im).zfill(12)}.jpg"
    image = Image.open(image_path).convert('RGB')
    image = transform(image)

    ann_ids = coco.get_annIds(im)
    annotations = coco.load_anns(ann_ids)

    for idx, model in enumerate(models):
        pred_boxes, pred_classes = get_detection(image, model)
        tp, fp, fn = calculate_matches(pred_boxes, pred_classes, annotations)
        TPs[idx] += tp
        FPs[idx] += fp
        FNs[idx] += fn

for idx, model in enumerate(models):
    precision = TPs[idx] / (TPs[idx] + FPs[idx]) if TPs[idx] + FPs[idx] > 0 else 0
    recall = TPs[idx] / (TPs[idx] + FNs[idx]) if TPs[idx] + FNs[idx] > 0 else 0
    print(f"Precision for model{idx}: {precision:.2f}")
    print(f"Recall for model{idx}: {recall:.2f}")
```

Output:

Model	Precision	Recall
model0	0.50	0.71
model1	0.52	0.74
model2	0.76	0.53
model3	0.80	0.26

REQUIRED FOR 691: GUEST LECTURES

Yu Zeng:

1. I wasn't really taking notes when the lecturer was speaking, but the lecturer's talk was creating and improving a model that can generate images from text. These images should somewhat mirror a real picture of what was asked. For example, Dr. Yu Zeng has examples of cartoon characters being generated from their model, the "accuracy" of the model would be how close that generated image is to the original picture of the cartoon character.
2. I asked a relatively simple question about her upcoming research. Just what exactly was the purpose of trying to recreate image of diseases/viruses, when you have REAL images of them? She said it would be to try and generate images, en masse, that can depict illnesses so that models that are used to detect certain illnesses have an image set to train on so that their performance gets better. Model for image data set generation so that the models that do disease detection can get better.
3. My favorite portion was honestly the part about her further research. Because as it stood, I didn't really see the utility in being able to generate pictures that looked like other pictures. But then when the lecturer brought up how her research could be useful in the health industry that's when I started to realize the applications. For example, another industry it could potentially help in is animation/entertainment. If the model is trained well enough to replicate characters, it could help with drawing the different still frames for things like anime which may help quicken the process of animating them into episodes (just a theory).
4. Y. Zeng, Z. Lin, J. Zhang, Q. Liu, J. Collomosse, J. Kuen, V. Patel, "Scenecomposer: Any-level semantic image synthesis," CVPR, 2023 (Hightlight, top 2.5%)
   Y. Zeng, V. M. Patel, H. Wang, X. Huang, T. Wang, M. Liu, Y. Balaji, "Jedi: Joint-image diffusion models for finetuning-free personalized text-to-image generation," CVPR, 2024.