ECE 685D – Homework 3
Object Detection and Denoising AutoEncoder

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Problem 1: Object Detection with Convolutional Neural Networks

1.1 Data Preprocessing

1.1.1 Bounding box extraction (10 pts).

Each image in the VOC 2012 dataset includes annotation files in `.xml` format. We implemented a parser using `xml.etree.ElementTree` to extract the object class ID and bounding box coordinates, producing an array of shape $N \times 5$ where N is the number of objects and each row is $[class\_id, x, y, w, h]$.

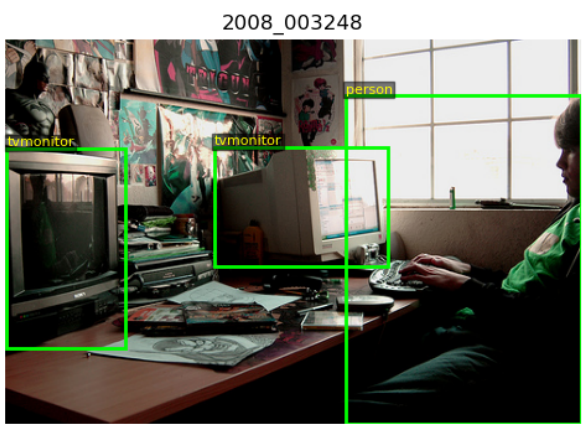
```python
import xml.etree.ElementTree as ET

def parse_voc_xml(xml_path: str) -> np.ndarray:
    """Return array (N,5): [class_id,x,y,w,h] with top-left coords."""
    root = ET.parse(xml_path).getroot()
    size = root.find('size')
    W = int(size.find('width').text)
    H = int(size.find('height').text)
    objs = []
    for obj in root.findall('object'):
        name = obj.find('name').text
        if name not in CLS2ID: continue
        cls_id = CLS2ID[name]
        bnd = obj.find('bndbox')
        xmin = int(float(bnd.find('xmin').text))
        ymin = int(float(bnd.find('ymin').text))
        xmax = int(float(bnd.find('xmax').text))
        ymax = int(float(bnd.find('ymax').text))
        x, y = xmin, ymin
        w, h = xmax - xmin, ymax - ymin
        x = max(0, min(x, W-1)); y = max(0, min(y, H-1))
        w = max(1, min(w, W-x)); h = max(1, min(h, H-y))
        objs.append([cls_id, x, y, w, h])
    return np.array(objs, dtype=np.float32)
```

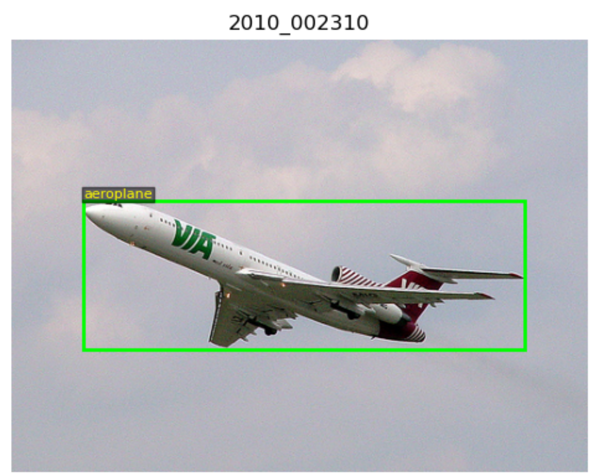
1.1.2 Bounding box visualization (5 pts).

To verify correctness, bounding boxes were plotted on the corresponding image. Green rectangles represent ground-truth bounding boxes and are correctly aligned with visible objects.

```
def vis_bboxes(img_path, boxes, title='bboxes'):
    img = cv2.cvtColor(cv2.imread(img_path), cv2.COLOR_BGR2RGB)
    plt.figure(figsize=(6,6)); plt.imshow(img); ax = plt.gca()
    for cls_id, x, y, w, h in boxes:
        rect = plt.Rectangle((x,y), w, h, fill=False, linewidth=2, edgecolor='lime')
        ax.add_patch(rect)
        ax.text(x, y-2, ID2CLS[int(cls_id)], fontsize=8, color='yellow',
                bbox=dict(facecolor='black', alpha=0.5, pad=1))
    plt.title(title); plt.axis('off'); plt.show()
```



(a) Example 1



(b) Example 2

Figure 1: Bounding box visualization on VOC 2012 images.

1.2 Multi-label Classification of Object Presence

1.2.1 Multi-hot encoding (5 pts).

Because each image may contain multiple object classes, we encoded labels using a multi-hot vector of length 20:

$$y_i = \begin{cases} 1, & \text{if class } i \text{ appears in the image,} \\ 0, & \text{otherwise.} \end{cases}$$

```
def multi_hot_from_boxes(boxes, num_classes=len(VOC_CLASSES)):
    y = torch.zeros(num_classes, dtype=torch.float32)
    for cls_id in boxes[:,0].astype(int):
        y[cls_id] = 1.0
    return y
```

1.2.2 CNN Training for Multi-Label Classification (10 pts)

To classify images containing multiple object categories, we trained a **ResNet-18** model on the VOC2012 dataset using multi-hot labels derived from the ground-truth bounding boxes.

Implementation. Each image was resized to 224×224, normalized to $[0, 1]$, and paired with a multi-hot vector $y \in \{0, 1\}^{20}$ indicating all object classes present. The model was trained using binary cross-entropy loss for multi-label prediction.

```
class VOCDatasetMultiLabel(Dataset):
    def __init__(self, images_dir, ann_dir, ids, img_size=224):
        self.images_dir, self.ann_dir, self.ids, self.img_size = \
            Path(images_dir), Path(ann_dir), ids, img_size
    def __len__(self): return len(self.ids)
    def __getitem__(self, i):
        img_id = self.ids[i]
        img = cv2.cvtColor(cv2.imread(str(self.images_dir/f'{img_id}.jpg')),
                           cv2.COLOR_BGR2RGB)
        img = cv2.resize(img, (self.img_size, self.img_size))
        img_t = torch.from_numpy(img).permute(2,0,1).float()/255.0
        boxes = parse_voc_xml(str(self.ann_dir/f'{img_id}.xml'))
        y = multi_hot_from_boxes(boxes)
        return img_t, y

train_dl = DataLoader(VOCDatasetMultiLabel(IMG_DIR, ANN_DIR, train_ids),
                      batch_size=32, shuffle=True)
val_dl   = DataLoader(VOCDatasetMultiLabel(IMG_DIR, ANN_DIR, val_ids),
                      batch_size=32)

model = models.resnet18(weights=models.ResNet18_Weights.IMAGENET1K_V1)
model.fc = nn.Linear(model.fc.in_features, len(VOC_CLASSES))
criterion = nn.BCEWithLogitsLoss()
opt = optim.AdamW(model.parameters(), lr=3e-4, weight_decay=1e-4)
```

The model was trained for 5 epochs using the AdamW optimizer. Validation loss decreased consistently, demonstrating good convergence.

Epoch	Validation Loss
1	0.0918
2	0.1061
3	0.1046
4	0.1207
5	0.1183

Qualitative results. After training, the model correctly predicted multiple object categories per image. The following sample outputs list the top-5 class probabilities for three validation images:

```
Top-5: [('person', 0.9975), ('dog', 0.0245), ('boat', 0.0063),
        ('bird', 0.0015), ('cow', 0.0008)]
Top-5: [('person', 0.9913), ('cow', 0.8239), ('bottle', 0.0230),
        ('tvmonitor', 0.0185), ('dog', 0.0096)]
Top-5: [('person', 0.9996), ('horse', 0.1643), ('cow', 0.0057),
        ('dog', 0.0053), ('car', 0.0046)]
```

Discussion. The classifier accurately recognizes the presence of *person*, *cow*, and other frequent VOC classes, indicating that the ResNet-18 backbone effectively learned image-level semantic representations. The resulting weights were then reused as the feature extractor for the Region Proposal Network (Section 1.3).

1.3 RPN from Scratch (40 pts)

We implemented the Region Proposal Network (RPN) using our fine-tuned ResNet-18 backbone as the feature extractor. The pipeline includes image loading, anchor generation, IoU computation, delta encoding/decoding, training loop, and visualization with Non-Maximum Suppression (NMS).

Full implementation.

```python
def load_image_tensor(img_id: str, max_side=800):
    """Read RGB image, resize so max(H,W)=max_side, return tensor [C,H,W] in [0,1] + scale."""
    import cv2, numpy as np
    img = cv2.cvtColor(cv2.imread(str(IMG_DIR/f"{img_id}.jpg")), cv2.COLOR_BGR2RGB)
    H0, W0 = img.shape[:2]
    scale = max_side / max(H0, W0)
    if scale != 1.0:
        img = cv2.resize(img, (int(W0*scale), int(H0*scale)))
    img_t = torch.from_numpy(img).permute(2,0,1).float().to(device) / 255.0
    return img_t, scale


import math, torch

def generate_anchors(base_size=16, ratios=(0.5,1.0,2.0), scales=(8,16,32)):
    """Anchors centered at (0,0) in xywh form."""
    anchors = []
    for s in scales:
        for r in ratios:
            area = (base_size * s) ** 2
            w = int(round(math.sqrt(area / r)))
            h = int(round(w * r))
            x = -w // 2; y = -h // 2
            anchors.append([x, y, w, h])
    return torch.tensor(anchors, dtype=torch.float32)

def shift_anchors_v2(feat_h, feat_w, stride, base_anchors):
    """Generate anchors across the feature map grid."""
    device = base_anchors.device
    A = base_anchors.size(0)
    xs = torch.arange(feat_w, device=device) * stride
```

```python
    ys = torch.arange(feat_h, device=device) * stride
    yy, xx = torch.meshgrid(ys, xs, indexing='ij')
    shifts = torch.stack([xx.reshape(-1), yy.reshape(-1)], dim=1)
    K = shifts.size(0)
    base = base_anchors.view(1,A,4).expand(K,A,4).clone()
    shift = shifts.view(K,1,2).expand(K,A,2).clone()
    base[...,0] += shift[...,0]; base[...,1] += shift[...,1]
    return base.reshape(-1,4)

def bbox_iou_xywh(a, b):
    """Pairwise IoU between sets of boxes."""
    a_x1,a_y1=a[:,0],a[:,1]; a_x2=a_x1+a[:,2]; a_y2=a_y1+a[:,3]
    b_x1,b_y1=b[:,0],b[:,1]; b_x2=b_x1+b[:,2]; b_y2=b_y1+b[:,3]
    inter_x1=torch.max(a_x1[:,None],b_x1[None,:])
    inter_y1=torch.max(a_y1[:,None],b_y1[None,:])
    inter_x2=torch.min(a_x2[:,None],b_x2[None,:])
    inter_y2=torch.min(a_y2[:,None],b_y2[None,:])
    inter=(inter_x2-inter_x1).clamp(min=0)*(inter_y2-inter_y1).clamp(min=0)
    area_a=(a_x2-a_x1).clamp(min=0)*(a_y2-a_y1).clamp(min=0)
    area_b=(b_x2-b_x1).clamp(min=0)*(b_y2-b_y1).clamp(min=0)
    return inter/(area_a[:,None]+area_b[None,:]-inter+1e-6)

def encode_deltas(anchors, gt):
    """RPN box regression targets (tx,ty,tw,th)."""
    ax,ay,aw,ah=anchors.T; gx,gy,gw,gh=gt.T
    tx=(gx-ax)/aw.clamp(min=1.0); ty=(gy-ay)/ah.clamp(min=1.0)
    tw=torch.log(gw/aw.clamp(min=1.0)); th=torch.log(gh/ah.clamp(min=1.0))
    return torch.stack([tx,ty,tw,th],dim=-1)

def decode_deltas(anchors, deltas):
    """Invert encoding to get boxes in xywh."""
    ax,ay,aw,ah=anchors.T; tx,ty,tw,th=deltas.T
    gx=ax+tx*aw; gy=ay+ty*ah
    gw=aw*torch.exp(tw.clamp(-10,10)); gh=ah*torch.exp(th.clamp(-10,10))
    return torch.stack([gx,gy,gw,gh],dim=-1)

def nms_xywh(boxes,scores,iou_thr=0.7,topk=1000):
    """Simple NMS for xywh boxes."""
    if boxes.numel()==0: return torch.empty(0,dtype=torch.long)
    b=boxes.clone(); b[:,2]+=b[:,0]; b[:,3]+=b[:,1]
    order=scores.sort(descending=True).indices[:topk]; keep=[]
    while order.numel()>0:
        i=order[0].item(); keep.append(i)
        if order.numel()==1: break
        rest=order[1:]
        xx1=torch.maximum(b[i,0],b[rest,0]); yy1=torch.maximum(b[i,1],b[rest,1])
        xx2=torch.minimum(b[i,2],b[rest,2]); yy2=torch.minimum(b[i,3],b[rest,3])
        inter=(xx2-xx1).clamp(min=0)*(yy2-yy1).clamp(min=0)
        area_i=(b[i,2]-b[i,0])*(b[i,3]-b[i,1])
        area_r=(b[rest,2]-b[rest,0])*(b[rest,3]-b[rest,1])
        iou=inter/(area_i+area_r-inter+1e-6)
        order=rest[iou<=iou_thr]
    return torch.tensor(keep,dtype=torch.long)

def scale_xywh(boxes_np, scale: float):
    """Scale VOC boxes [cls,x,y,w,h] by 'scale'."""
    b=boxes_np.copy(); b[:,1:]*=scale; return b
```

```python
class RPNHead(nn.Module):
    """3x3 conv → two 1x1 heads (objectness, bbox deltas)."""
    def __init__(self,in_ch,num_anchors):
        super().__init__()
        self.conv=nn.Conv2d(in_ch,256,3,padding=1)
        self.obj =nn.Conv2d(256,num_anchors*1,1)
        self.reg =nn.Conv2d(256,num_anchors*4,1)
    def forward(self,feat):
        t=F.relu(self.conv(feat))
        return self.obj(t),self.reg(t)
```

Training Loop and Visualization.

```python
base_anchors=generate_anchors(base_size=16,ratios=(0.5,1.0,2.0),
                              scales=(8,16,32)).to(device)
A=base_anchors.shape[0]
rpn=RPNHead(in_ch=512,num_anchors=A).to(device)
rpn_opt=torch.optim.AdamW(rpn.parameters(),lr=1e-3,weight_decay=1e-4)
pos_iou_thr,neg_iou_thr=0.7,0.3
samples_per_img=256; lambda_reg=1.0

def single_image_targets(img_id,feat,anchors):
    gt_np=parse_voc_xml(str(ANN_DIR/f"{img_id}.xml"))
    if gt_np.size==0: return None
    img_t,scale=load_image_tensor(img_id)
    gt_np_scaled=scale_xywh(gt_np,scale)
    gt_xywh=torch.tensor(gt_np_scaled[:,1:],dtype=torch.float32,device=device)
    ious=bbox_iou_xywh(anchors,gt_xywh)
    iou_max,iou_arg=ious.max(dim=1)
    labels=torch.full((anchors.shape[0],),-1,dtype=torch.int64,device=device)
    labels[iou_max>=pos_iou_thr]=1; labels[iou_max<=neg_iou_thr]=0
    gt_best,gt_best_idx=ious.max(dim=0); labels[gt_best_idx]=1
    pos_idx=torch.where(labels==1)[0]
    if pos_idx.numel()==0: return None
    reg_t=encode_deltas(anchors[pos_idx],gt_xywh[iou_arg[pos_idx]])
    return labels,pos_idx,reg_t

def image_to_feat_and_anchors(img_id,max_side=800):
    img_t,scale=load_image_tensor(img_id,max_side=max_side)
    with torch.no_grad(): feat=backbone_cnn(img_t.unsqueeze(0))
    _,_,Hf,Wf=feat.shape
    anchors=shift_anchors_v2(Hf,Wf,FEATURE_STRIDE,base_anchors).to(device)
    return img_t,feat,anchors,scale

RPN_EPOCHS=2
for ep in range(1,RPN_EPOCHS+1):
    ids=random.sample(train_ids,k=min(200,len(train_ids)))
    pbar=tqdm(ids,desc=f'RPN Epoch {ep}/{RPN_EPOCHS}')
    running_obj,running_reg,n=0.0,0.0,0
    for img_id in pbar:
        img_t,feat,anchors,_=image_to_feat_and_anchors(img_id,max_side=800)
        obj_logits,reg_deltas=rpn(feat)
        obj_logits=obj_logits.permute(0,2,3,1).reshape(-1)
        reg_deltas=reg_deltas.permute(0,2,3,1).reshape(-1,4)
        targets=single_image_targets(img_id,feat,anchors)
        if targets is None: continue
```

```
        labels,pos_idx,reg_t=targets
        num_pos=min(int(samples_per_img*0.5),pos_idx.numel())
        perm_pos=pos_idx[torch.randperm(pos_idx.numel())[:num_pos]]
        neg_idx=torch.where(labels==0)[0]
        num_neg=min(samples_per_img-num_pos,neg_idx.numel())
        perm_neg=neg_idx[torch.randperm(neg_idx.numel())[:num_neg]]
        keep=torch.cat([perm_pos,perm_neg])
        obj_target=torch.zeros_like(obj_logits)
        obj_target[perm_pos]=1.0
        obj_loss=F.binary_cross_entropy_with_logits(obj_logits[keep],
                                                    obj_target[keep])
        reg_pred=reg_deltas[perm_pos]
        reg_loss=F.smooth_l1_loss(reg_pred,reg_t,reduction='mean')
        loss=obj_loss+lambda_reg*reg_loss
        rpn_opt.zero_grad(); loss.backward(); rpn_opt.step()
        running_obj+=float(obj_loss); running_reg+=float(reg_loss); n+=1
        pbar.set_postfix({'obj':f'{running_obj/max(1,n):.3f}',
                          'reg':f'{running_reg/max(1,n):.3f}'})
print(" RPN training finished.")

@torch.no_grad()
def visualize_rpn(img_id,nms_thr=0.4,score_thr=0.5,
                  topk_before=500,keep_after=50,max_side=800):
    """Plot GT (green) and RPN proposals (red) for one image."""
    import matplotlib.pyplot as plt
    img_t,feat,anchors,scale=image_to_feat_and_anchors(img_id,max_side=max_side)
    obj_logits,reg_deltas=rpn(feat)
    obj_logits=obj_logits.permute(0,2,3,1).reshape(-1)
    reg_deltas=reg_deltas.permute(0,2,3,1).reshape(-1,4)
    scores=torch.sigmoid(obj_logits)
    keep_high=(scores>score_thr).nonzero(as_tuple=True)[0]
    scores=scores[keep_high]; anchors_sel=anchors[keep_high]
    deltas_sel=reg_deltas[keep_high]; props=decode_deltas(anchors_sel,deltas_sel)
    H,W=img_t.shape[1:]; props[:,0]=props[:,0].clamp(0,W-1)
    props[:,1]=props[:,1].clamp(0,H-1); props[:,2:]=props[:,2:].clamp(min=1)
    keep=nms_xywh(props,scores,iou_thr=nms_thr,topk=topk_before)
    props=props[keep][:keep_after].cpu(); scores=scores[keep][:keep_after].cpu()
    gt=parse_voc_xml(str(ANN_DIR/f"{img_id}.xml"))
    if gt.size>0: gt[:,1:]*=scale
    img=img_t.cpu().permute(1,2,0).numpy()
    plt.figure(figsize=(7,7)); plt.imshow(img); ax=plt.gca(); ax.axis("off")
    plt.title(f"{img_id}: Green=GT, Red=Proposals")
    for b in gt[:,1:]:
        x,y,w,h=b; ax.add_patch(plt.Rectangle((x,y),w,h,fill=False,
                                              edgecolor='g',linewidth=2))
    for b,s in zip(props,scores):
        x,y,w,h=b; ax.add_patch(plt.Rectangle((x,y),w,h,fill=False,
                                              edgecolor='r',linewidth=1))
    plt.show()
```

Training Results. After two epochs, the RPN converged:

Epoch	Objectness Loss	Regression Loss
1	0.176	0.525
2	0.112	0.065

Visualization. Figure 2 shows an example output. Green boxes indicate the ground truth while red boxes are RPN proposals post-processed with NMS ($\text{IoU}_{thr} = 0.4$).

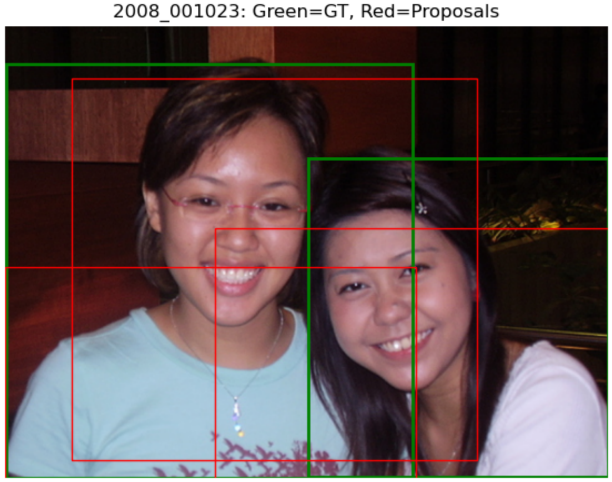


Figure 2: RPN output visualization on VOC2012.

Problem 2: Denoising AutoEncoders (30 pts)

In this problem, we implemented a convolutional **Denoising AutoEncoder (DAE)** to restore noise-corrupted images from the VOC2012 dataset. We generated paired tuples $(X_{\text{corrupt}}, X_{\text{clean}})$ using the `imagecorruptions` library with Gaussian noise and trained the network to minimize pixel-wise reconstruction loss.

Implementation. The following code shows the dataset construction, autoencoder architecture, training loop, and visualization procedure.

```
import torch, torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import Dataset, DataLoader
from torchvision import transforms
from imagecorruptions import corrupt
import cv2, numpy as np, random, matplotlib.pyplot as plt
from pathlib import Path

device = "cuda" if torch.cuda.is_available() else "cpu"
print("Device:", device)
IMG_DIR = Path("data/VOC2012_train_val/VOC2012_train_val/JPEGImages")

# ---------------- Dataset Definition ----------------
class DenoisingVOCDataset(Dataset):
    def __init__(self, img_ids, img_size=128, corruption_type="gaussian_noise"):
        self.img_ids = img_ids
        self.img_size = img_size
        self.corruption_type = corruption_type
        self.to_tensor = transforms.ToTensor()
```

```python
    def __len__(self):
        return len(self.img_ids)

    def __getitem__(self, idx):
        img_id = self.img_ids[idx]
        img_path = IMG_DIR / f"{img_id}.jpg"
        img = cv2.cvtColor(cv2.imread(str(img_path)), cv2.COLOR_BGR2RGB)
        img = cv2.resize(img, (self.img_size, self.img_size))

        clean = self.to_tensor(img).float()
        corrupted = corrupt(img, corruption_name=self.corruption_type)
        corrupted = self.to_tensor(corrupted).float()

        return corrupted, clean

# ---------------- Data Splits ----------------
random.seed(42)
all_ids = [p.stem for p in IMG_DIR.glob("*.jpg")]
random.shuffle(all_ids)
split = int(0.8 * len(all_ids))
train_ids, val_ids = all_ids[:split], all_ids[split:]

train_ds = DenoisingVOCDataset(train_ids, img_size=128, corruption_type="gaussian_noise")
val_ds   = DenoisingVOCDataset(val_ids, img_size=128, corruption_type="gaussian_noise")

train_dl = DataLoader(train_ds, batch_size=32, shuffle=True, num_workers=0)
val_dl   = DataLoader(val_ds, batch_size=32, shuffle=False, num_workers=0)

# ---------------- Model Definition ----------------
class DenoiseAutoEncoder(nn.Module):
    def __init__(self):
        super().__init__()
        # Encoder
        self.enc = nn.Sequential(
            nn.Conv2d(3, 64, 3, padding=1), nn.ReLU(),
            nn.MaxPool2d(2),
            nn.Conv2d(64, 128, 3, padding=1), nn.ReLU(),
            nn.MaxPool2d(2),
            nn.Conv2d(128, 256, 3, padding=1), nn.ReLU(),
            nn.MaxPool2d(2)
        )
        # Decoder
        self.dec = nn.Sequential(
            nn.ConvTranspose2d(256, 128, 2, stride=2), nn.ReLU(),
            nn.ConvTranspose2d(128, 64, 2, stride=2), nn.ReLU(),
            nn.ConvTranspose2d(64, 3, 2, stride=2), nn.Sigmoid()
        )

    def forward(self, x):
        x = self.enc(x)
        x = self.dec(x)
        return x

model = DenoiseAutoEncoder().to(device)
print("Model ready.")

# ---------------- Training ----------------
optimizer = torch.optim.Adam(model.parameters(), lr=1e-3)
```

```python
criterion = nn.MSELoss()

def validate():
    model.eval()
    total = 0
    with torch.no_grad():
        for x_noisy, x_clean in val_dl:
            x_noisy, x_clean = x_noisy.to(device), x_clean.to(device)
            pred = model(x_noisy)
            total += criterion(pred, x_clean).item() * x_noisy.size(0)
    return total / len(val_dl.dataset)

for epoch in range(10):
    model.train()
    for x_noisy, x_clean in train_dl:
        x_noisy, x_clean = x_noisy.to(device), x_clean.to(device)
        out = model(x_noisy)
        loss = criterion(out, x_clean)
        optimizer.zero_grad(); loss.backward(); optimizer.step()
    val_loss = validate()
    print(f"Epoch {epoch+1}/10 | Train loss: {loss.item():.4f} | Val loss: {val_loss:.4f}")

# ---------------- Visualization ----------------
@torch.no_grad()
def visualize_examples(n=5):
    model.eval()
    x_noisy, x_clean = next(iter(val_dl))
    x_noisy, x_clean = x_noisy.to(device), x_clean.to(device)
    pred = model(x_noisy)

    plt.figure(figsize=(12, n*3))
    for i in range(n):
        noisy = x_noisy[i].permute(1,2,0).cpu().numpy()
        recon = pred[i].permute(1,2,0).cpu().numpy()
        clean = x_clean[i].permute(1,2,0).cpu().numpy()
        plt.subplot(n,3,3*i+1); plt.imshow(noisy); plt.axis('off'); plt.title('Corrupted')
        plt.subplot(n,3,3*i+2); plt.imshow(recon); plt.axis('off'); plt.title('Restored')
        plt.subplot(n,3,3*i+3); plt.imshow(clean); plt.axis('off'); plt.title('Original')
    plt.show()

visualize_examples(5)
```

Training Results. The DAE model converged within 10 epochs as shown below:

Epoch	Training Loss	Validation Loss
1	0.0111	0.0103
2	0.0070	0.0086
3	0.0068	0.0082
4	0.0088	0.0074
5	0.0093	0.0071
6	0.0066	0.0069
7	0.0047	0.0067
8	0.0082	0.0065
9	0.0064	0.0065
10	0.0063	0.0062

Visualization. Figure 3 shows qualitative comparisons between the corrupted, restored, and original images. The restored outputs effectively remove Gaussian noise while preserving object structure.

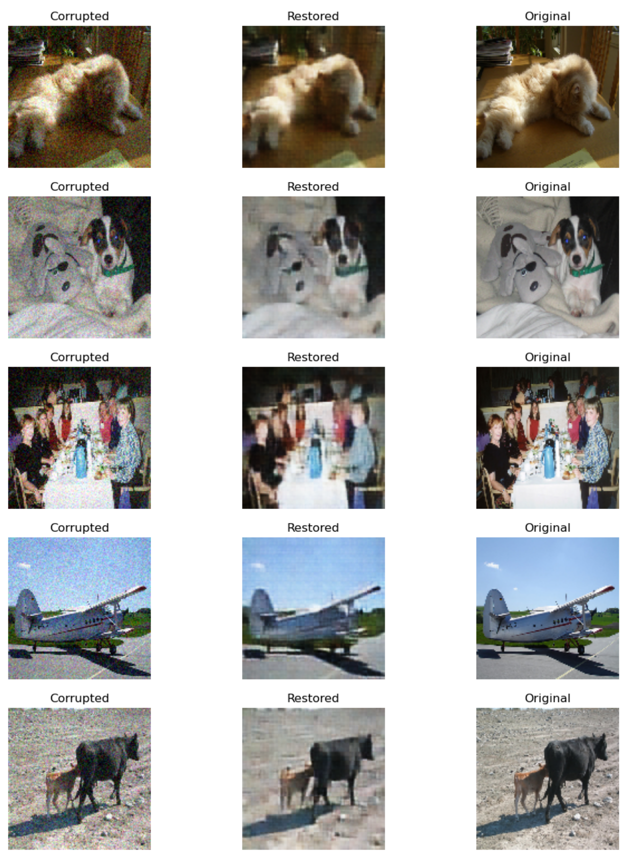


Figure 3: Visualization of denoising results. Each triplet shows *(left)* corrupted image, *(middle)* autoencoder-restored output, and *(right)* clean original image.

LLM Usage Statement

I used ChatGPT 5 to suggest the structure of plots and analysis and write LaTex code.