```
# Project: Fine-Grained Bird Species Classification on CUB-200-2011
# Compare: Pretrained ResNet-18 vs Pretrained ViT

# ============================================================================
# 1. Install dependencies (if needed in Colab)
# ============================================================================
!pip install -q transformers datasets torch torchvision scikit-learn matplotlib pillow tqdm evaluate
!pip install seaborn
# ============================================================================
# 2. Import libraries
# ============================================================================
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, random_split
from torchvision import models, transforms
from transformers import ViTForImageClassification
from datasets import load_dataset
from tqdm import tqdm
from sklearn.metrics import accuracy_score, top_k_accuracy_score, classification_report, confusion_matrix
from collections import Counter
import numpy as np
import matplotlib.pyplot as plt
import time
import seaborn as sns
import pandas as pd
```

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Requirement already satisfied: seaborn in /usr/local/lib/python3.12/dist-packages (0.13.2)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in /usr/local/lib/python3.12/dist-packages (from seaborn) (2.0.2)
Requirement already satisfied: pandas>=1.2 in /usr/local/lib/python3.12/dist-packages (from seaborn) (2.2.2)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in /usr/local/lib/python3.12/dist-packages (from seaborn) (3.10.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.12/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (1.3.
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.12/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.12/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (4.6
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.12/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (1.4
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.12/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (26.0)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.12/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.12/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (3.3.
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.12/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/dist-packages (from pandas>=1.2->seaborn) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.12/dist-packages (from pandas>=1.2->seaborn) (2025.3)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.12/dist-packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>=3.4->
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# ============================================================================
# 3. Device & Hyperparameters
# ============================================================================
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")

BATCH_SIZE = 32   # Compromise between originals (16 for ViT, 64 for ResNet)
NUM_EPOCHS = 30     # Balanced for comparison
NUM_CLASSES = 200

models_config = [
    {"name": "resnet18", "pretrained": True, "lr": 0.001},
    {"name": "vit", "pretrained": True, "lr": 3e-5}
]
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Using device: cuda
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# ============================================================================
# 4. Load Dataset from Hugging Face
# ============================================================================
print("Loading dataset...")
hf_dataset = load_dataset("bentrevett/caltech-ucsd-birds-200-2011")

class_names = hf_dataset['train'].features['label'].names   # Get class names for reporting

class CUBDataset(torch.utils.data.Dataset):
    def __init__(self, hf_dataset, transform=None):
        self.hf_dataset = hf_dataset
        self.transform = transform

    def __len__(self):
        return len(self.hf_dataset)

    def __getitem__(self, idx):
        item = self.hf_dataset[idx]
        image = item['image'].convert('RGB')
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                label = item['label']
                if self.transform:
                        image = self.transform(image)
                return image, label

train_transform = transforms.Compose([
        transforms.Resize(256),
        transforms.RandomResizedCrop(224),
        transforms.RandomHorizontalFlip(),
        transforms.RandomRotation(15),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])

test_transform = transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])

full_train_ds = CUBDataset(hf_dataset['train'], train_transform)
test_ds = CUBDataset(hf_dataset['test'], test_transform)

train_size = int(0.85 * len(full_train_ds))
val_size = len(full_train_ds) - train_size
train_ds, val_ds = random_split(full_train_ds, [train_size, val_size])

train_loader = DataLoader(train_ds, batch_size=BATCH_SIZE, shuffle=True, num_workers=2, pin_memory=True)
val_loader = DataLoader(val_ds, batch_size=BATCH_SIZE, shuffle=False, num_workers=2, pin_memory=True)
test_loader = DataLoader(test_ds, batch_size=BATCH_SIZE, shuffle=False, num_workers=2, pin_memory=True)

print(f"Train samples: {len(train_ds)}, Val samples: {len(val_ds)}, Test samples: {len(test_ds)}")
print(f"Num classes: {NUM_CLASSES}, Example classes: {class_names[:5]}...")
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Loading dataset...
Train samples: 5094, Val samples: 900, Test samples: 5794
Num classes: 200, Example classes: ['001.Black_footed_Albatross', '002.Laysan_Albatross', '003.Sooty_Albatross', '004.Groove_billed_Ani'
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# ============================================================================
# 5. Train and Evaluate Functions (Unified for both models)
# ============================================================================
def train_epoch(model, loader, criterion, optimizer, scaler, device, model_name):
        model.train()
        total_loss, correct, total = 0.0, 0, 0
        for images, labels in tqdm(loader, desc="Training"):
                images, labels = images.to(device), labels.to(device)
                optimizer.zero_grad()
                with torch.cuda.amp.autocast(enabled=True):
                        if model_name == "vit":
                                outputs = model(pixel_values=images).logits
                        else:
                                outputs = model(images)
                        loss = criterion(outputs, labels)
                scaler.scale(loss).backward()
                scaler.step(optimizer)
                scaler.update()
                total_loss += loss.item() * images.size(0)
                pred = outputs.argmax(dim=1)
                correct += (pred == labels).sum().item()
                total += images.size(0)
        return total_loss / total, correct / total

def evaluate(model, loader, criterion, device, model_name, is_test=False):
        model.eval()
        total_loss, correct, total = 0.0, 0, 0
        all_preds, all_labels, all_logits = [], [], []
        with torch.no_grad():
                for images, labels in tqdm(loader, desc="Evaluating"):
                        images, labels = images.to(device), labels.to(device)
                        if model_name == "vit":
                                outputs = model(pixel_values=images).logits
                        else:
                                outputs = model(images)
                        loss = criterion(outputs, labels)
                        total_loss += loss.item() * images.size(0)
                        pred = outputs.argmax(dim=1)
                        correct += (pred == labels).sum().item()
                        total += images.size(0)
                        all_preds.extend(pred.cpu().numpy())
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                all_labels.extend(labels.cpu().numpy())
                if is_test:
                        all_logits.extend(outputs.cpu().numpy())    # For top-5
        acc = correct / total
        loss = total_loss / total
        top5_acc = top_k_accuracy_score(all_labels, all_logits, k=5) if is_test else None
        return loss, acc, top5_acc, all_preds, all_labels
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# ======================================================================
# 6. Main Training Loop
# ======================================================================
all_history = {}
test_results = {}
for config in models_config:
        name = config["name"]
        print(f"\n=== Training {name} ===")
        if name == "resnet18":
                model = models.resnet18(pretrained=config["pretrained"])
                model.fc = nn.Linear(model.fc.in_features, NUM_CLASSES)
                # Freeze all except last layer and classifier (as in original ResNet)
                for param in model.parameters():
                        param.requires_grad = False
                for param in model.layer4.parameters():
                        param.requires_grad = True
                for param in model.fc.parameters():
                        param.requires_grad = True

        elif name == "vit":
                model = ViTForImageClassification.from_pretrained(
                        "google/vit-base-patch16-224-in21k",
                        num_labels=NUM_CLASSES,
                        ignore_mismatched_sizes=True
                )
                # No freezing in original ViT, so train all with small LR

        model = model.to(device)
        criterion = nn.CrossEntropyLoss(label_smoothing=0.1)
        optimizer = optim.AdamW(model.parameters(), lr=config["lr"], weight_decay=0.01)
        scaler = torch.cuda.amp.GradScaler(enabled=True)
        scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='max', factor=0.5, patience=2)

        history = {"train_loss": [], "train_acc": [], "val_loss": [], "val_acc": [], "train_time": []}
        best_val_acc = 0.0
        t_start = time.time()

        for epoch in range(NUM_EPOCHS):
                tr_loss, tr_acc = train_epoch(model, train_loader, criterion, optimizer, scaler, device, name)
                va_loss, va_acc, _, _, _ = evaluate(model, val_loader, criterion, device, name)
                scheduler.step(va_acc)
                history["train_loss"].append(tr_loss)
                history["train_acc"].append(tr_acc)
                history["val_loss"].append(va_loss)
                history["val_acc"].append(va_acc)
                epoch_time = time.time() - t_start
                history["train_time"].append(epoch_time)
                print(f"Epoch {epoch+1}/{NUM_EPOCHS} | Train Loss: {tr_loss:.4f} Acc: {tr_acc:.4f} | Val Loss: {va_loss:.4f}

                if va_acc > best_val_acc:
                        best_val_acc = va_acc
                        torch.save(model.state_dict(), f"best_{name}.pth")

        total_train_time = time.time() - t_start
        print(f"Total training time for {name}: {total_train_time:.1f}s")

        # Load best model for test
        model.load_state_dict(torch.load(f"best_{name}.pth", map_location=device))
        te_loss, te_acc, te_top5_acc, te_preds, te_labels = evaluate(model, test_loader, criterion, device, name, is_test=Tr
        report = classification_report(te_labels, te_preds, target_names=class_names, output_dict=True)
        macro_f1 = report['macro avg']['f1-score']

        test_results[name] = {
                "acc": te_acc,
                "top5_acc": te_top5_acc,
                "macro_f1": macro_f1,
                "train_time": total_train_time,
                "preds": te_preds,
                "labels": te_labels
        }
        all_history[name] = history

        # Per-model error analysis (top-5 confused pairs)
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errors = [(true, pred) for true, pred in zip(te_labels, te_preds) if true != pred]
if errors:
        most_common_errors = Counter(errors).most_common(5)
        print(f"Top 5 confused pairs for {name} (True → Predicted):")
        for (true_label, pred_label), count in most_common_errors:
                true_name = class_names[true_label]
                pred_name = class_names[pred_label]
                print(f"   {true_name} → {pred_name} : {count} times")
```

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=== Training resnet18 ===
/usr/local/lib/python3.12/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.
  warnings.warn(
/usr/local/lib/python3.12/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for
  warnings.warn(msg)
/tmp/ipython-input-3482151153.py:31: FutureWarning: `torch.cuda.amp.GradScaler(args...)` is deprecated. Please use `torch.amp.GradScaler
  scaler = torch.cuda.amp.GradScaler(enabled=True)
Training:   0%|          | 0/160 [00:00<?, ?it/s]/tmp/ipython-input-838357888.py:10: FutureWarning: `torch.cuda.amp.autocast(args...)` i
  with torch.cuda.amp.autocast(enabled=True):
Training: 100%|██████████| 160/160 [00:59<00:00,  2.67it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.16it/s]
Epoch 1/30 | Train Loss: 4.4131 Acc: 0.1227 | Val Loss: 3.6645 Acc: 0.2500
Training: 100%|██████████| 160/160 [00:32<00:00,  4.98it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.32it/s]
Epoch 2/30 | Train Loss: 3.3113 Acc: 0.3147 | Val Loss: 3.2139 Acc: 0.3178
Training: 100%|██████████| 160/160 [00:32<00:00,  4.93it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.32it/s]
Epoch 3/30 | Train Loss: 2.9849 Acc: 0.4009 | Val Loss: 3.1517 Acc: 0.3944
Training: 100%|██████████| 160/160 [00:35<00:00,  4.52it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.48it/s]
Epoch 4/30 | Train Loss: 2.7822 Acc: 0.4609 | Val Loss: 3.0364 Acc: 0.3944
Training: 100%|██████████| 160/160 [00:34<00:00,  4.69it/s]
Evaluating: 100%|██████████| 29/29 [00:05<00:00,  5.18it/s]
Epoch 5/30 | Train Loss: 2.5847 Acc: 0.5261 | Val Loss: 2.8577 Acc: 0.4511
Training: 100%|██████████| 160/160 [00:35<00:00,  4.49it/s]
Evaluating: 100%|██████████| 29/29 [00:05<00:00,  5.22it/s]
Epoch 6/30 | Train Loss: 2.4598 Acc: 0.5626 | Val Loss: 2.8177 Acc: 0.4744
Training: 100%|██████████| 160/160 [00:33<00:00,  4.77it/s]
Evaluating: 100%|██████████| 29/29 [00:05<00:00,  5.25it/s]
Epoch 7/30 | Train Loss: 2.3739 Acc: 0.5885 | Val Loss: 2.7621 Acc: 0.4811
Training: 100%|██████████| 160/160 [00:33<00:00,  4.81it/s]
Evaluating: 100%|██████████| 29/29 [00:05<00:00,  5.07it/s]
Epoch 8/30 | Train Loss: 2.2520 Acc: 0.6229 | Val Loss: 2.7941 Acc: 0.4767
Training: 100%|██████████| 160/160 [00:35<00:00,  4.48it/s]
Evaluating: 100%|██████████| 29/29 [00:05<00:00,  5.06it/s]
Epoch 9/30 | Train Loss: 2.2141 Acc: 0.6378 | Val Loss: 2.7987 Acc: 0.4822
Training: 100%|██████████| 160/160 [00:33<00:00,  4.77it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.66it/s]
Epoch 10/30 | Train Loss: 2.1279 Acc: 0.6639 | Val Loss: 2.8092 Acc: 0.4744
Training: 100%|██████████| 160/160 [00:33<00:00,  4.85it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.35it/s]
Epoch 11/30 | Train Loss: 2.0650 Acc: 0.6959 | Val Loss: 2.7566 Acc: 0.4922
Training: 100%|██████████| 160/160 [00:32<00:00,  4.89it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.32it/s]
Epoch 12/30 | Train Loss: 2.0473 Acc: 0.6985 | Val Loss: 2.8087 Acc: 0.4767
Training: 100%|██████████| 160/160 [00:32<00:00,  4.88it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.30it/s]
Epoch 13/30 | Train Loss: 2.0067 Acc: 0.7087 | Val Loss: 2.7345 Acc: 0.5167
Training: 100%|██████████| 160/160 [00:32<00:00,  4.86it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.25it/s]
Epoch 14/30 | Train Loss: 1.9838 Acc: 0.7191 | Val Loss: 2.8173 Acc: 0.4822
Training: 100%|██████████| 160/160 [00:32<00:00,  4.90it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.36it/s]
Epoch 15/30 | Train Loss: 1.9302 Acc: 0.7346 | Val Loss: 2.7303 Acc: 0.5144
Training: 100%|██████████| 160/160 [00:32<00:00,  4.91it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.21it/s]
Epoch 16/30 | Train Loss: 1.8801 Acc: 0.7532 | Val Loss: 2.7800 Acc: 0.4989
Training: 100%|██████████| 160/160 [00:33<00:00,  4.81it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.37it/s]
Epoch 17/30 | Train Loss: 1.7388 Acc: 0.8074 | Val Loss: 2.5005 Acc: 0.5678
Training: 100%|██████████| 160/160 [00:32<00:00,  4.94it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.35it/s]
Epoch 18/30 | Train Loss: 1.6760 Acc: 0.8204 | Val Loss: 2.5576 Acc: 0.5467
Training: 100%|██████████| 160/160 [00:32<00:00,  4.94it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.28it/s]
Epoch 19/30 | Train Loss: 1.6369 Acc: 0.8316 | Val Loss: 2.6019 Acc: 0.5567
Training: 100%|██████████| 160/160 [00:32<00:00,  4.96it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.33it/s]
Epoch 20/30 | Train Loss: 1.6554 Acc: 0.8251 | Val Loss: 2.5767 Acc: 0.5544
Training: 100%|██████████| 160/160 [00:35<00:00,  4.53it/s]
Evaluating: 100%|██████████| 29/29 [00:05<00:00,  4.98it/s]
Epoch 21/30 | Train Loss: 1.5740 Acc: 0.8543 | Val Loss: 2.5261 Acc: 0.5878
Training: 100%|██████████| 160/160 [00:35<00:00,  4.50it/s]
Evaluating: 100%|██████████| 29/29 [00:05<00:00,  5.01it/s]
Epoch 22/30 | Train Loss: 1.5183 Acc: 0.8679 | Val Loss: 2.5261 Acc: 0.5744
Training: 100%|██████████| 160/160 [00:34<00:00,  4.67it/s]
Evaluating: 100%|██████████| 29/29 [00:05<00:00,  5.17it/s]
Epoch 23/30 | Train Loss: 1.5095 Acc: 0.8687 | Val Loss: 2.5133 Acc: 0.5700
Training: 100%|██████████| 160/160 [00:34<00:00,  4.65it/s]
Evaluating: 100%|██████████| 29/29 [00:05<00:00,  5.11it/s]
Epoch 24/30 | Train Loss: 1.5183 Acc: 0.8644 | Val Loss: 2.5986 Acc: 0.5667
Training: 100%|██████████| 160/160 [00:33<00:00,  4.71it/s]
Evaluating: 100%|██████████| 29/29 [00:05<00:00,  4.90it/s]
Epoch 25/30 | Train Loss: 1.5080 Acc: 0.8724 | Val Loss: 2.5243 Acc: 0.5800
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Training: 100%|██████████| 160/160 [00:34<00:00,  4.66it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.19it/s]
Epoch 26/30 | Train Loss: 1.4747 Acc: 0.8820 | Val Loss: 2.5739 Acc: 0.5578
Training: 100%|██████████| 160/160 [00:33<00:00,  4.81it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.28it/s]
Epoch 27/30 | Train Loss: 1.4515 Acc: 0.8816 | Val Loss: 2.5614 Acc: 0.5733
Training: 100%|██████████| 160/160 [00:33<00:00,  4.84it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.18it/s]
Epoch 28/30 | Train Loss: 1.4677 Acc: 0.8783 | Val Loss: 2.5488 Acc: 0.5578
Training: 100%|██████████| 160/160 [00:33<00:00,  4.84it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.28it/s]
Epoch 29/30 | Train Loss: 1.4435 Acc: 0.8850 | Val Loss: 2.6222 Acc: 0.5511
Training: 100%|██████████| 160/160 [00:33<00:00,  4.78it/s]
Evaluating: 100%|██████████| 29/29 [00:06<00:00,  4.53it/s]
Epoch 30/30 | Train Loss: 1.4342 Acc: 0.8912 | Val Loss: 2.5862 Acc: 0.5611
Total training time for resnet18: 1225.9s
Evaluating: 100%|██████████| 182/182 [00:30<00:00,  6.01it/s]
Top 5 confused pairs for resnet18 (True → Predicted):
  025.Pelagic_Cormorant → 023.Brandt_Cormorant : 14 times
  051.Horned_Grebe → 050.Eared_Grebe : 12 times
  107.Common_Raven → 029.American_Crow : 11 times
  185.Bohemian_Waxwing → 186.Cedar_Waxwing : 10 times
  102.Western_Wood_Pewee → 040.Olive_sided_Flycatcher : 9 times

=== Training vit ===
Loading weights: 100%                                198/198 [00:00<00:00, 399.68it/s, Materializing param=vit.layernorm.weight]
ViTForImageClassification LOAD REPORT from: google/vit-base-patch16-224-in21k
Key                 | Status     |
--------------------+------------+-
pooler.dense.weight | UNEXPECTED |
pooler.dense.bias   | UNEXPECTED |
classifier.bias     | MISSING    |
classifier.weight   | MISSING    |

Notes:
- UNEXPECTED  :can be ignored when loading from different task/architecture; not ok if you expect identical arch.
- MISSING  :those params were newly initialized because missing from the checkpoint. Consider training on your downstream task.
/tmp/ipython-input-3482151153.py:31: FutureWarning: `torch.cuda.amp.GradScaler(args...)` is deprecated. Please use `torch.amp.GradScaler
  scaler = torch.cuda.amp.GradScaler(enabled=True)
Training:   0%|          | 0/160 [00:00<?, ?it/s]/tmp/ipython-input-838357888.py:10: FutureWarning: `torch.cuda.amp.autocast(args...)` i
  with torch.cuda.amp.autocast(enabled=True):
Training: 100%|██████████| 160/160 [00:48<00:00,  3.33it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.74it/s]
Epoch 1/30 | Train Loss: 5.1987 Acc: 0.0870 | Val Loss: 5.0642 Acc: 0.2622
Training: 100%|██████████| 160/160 [00:47<00:00,  3.34it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.77it/s]
Epoch 2/30 | Train Loss: 4.8882 Acc: 0.4321 | Val Loss: 4.7495 Acc: 0.5022
Training: 100%|██████████| 160/160 [00:47<00:00,  3.38it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.80it/s]
Epoch 3/30 | Train Loss: 4.5550 Acc: 0.5850 | Val Loss: 4.4486 Acc: 0.5811
Training: 100%|██████████| 160/160 [00:46<00:00,  3.41it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.75it/s]
Epoch 4/30 | Train Loss: 4.2411 Acc: 0.6466 | Val Loss: 4.1845 Acc: 0.5711
Training: 100%|██████████| 160/160 [00:47<00:00,  3.38it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.82it/s]
Epoch 5/30 | Train Loss: 3.9398 Acc: 0.6920 | Val Loss: 3.8888 Acc: 0.6311
Training: 100%|██████████| 160/160 [00:47<00:00,  3.40it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.73it/s]
Epoch 6/30 | Train Loss: 3.6514 Acc: 0.7189 | Val Loss: 3.6511 Acc: 0.6344
Training: 100%|██████████| 160/160 [00:48<00:00,  3.33it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.78it/s]
Epoch 7/30 | Train Loss: 3.3669 Acc: 0.7313 | Val Loss: 3.3957 Acc: 0.6467
Training: 100%|██████████| 160/160 [00:47<00:00,  3.37it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.75it/s]
Epoch 8/30 | Train Loss: 3.0898 Acc: 0.7585 | Val Loss: 3.1805 Acc: 0.6378
Training: 100%|██████████| 160/160 [00:47<00:00,  3.35it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.79it/s]
Epoch 9/30 | Train Loss: 2.8423 Acc: 0.7774 | Val Loss: 2.9149 Acc: 0.6656
Training: 100%|██████████| 160/160 [00:47<00:00,  3.37it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.77it/s]
Epoch 10/30 | Train Loss: 2.6150 Acc: 0.7880 | Val Loss: 2.7135 Acc: 0.6867
Training: 100%|██████████| 160/160 [00:47<00:00,  3.35it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.78it/s]
Epoch 11/30 | Train Loss: 2.3871 Acc: 0.8078 | Val Loss: 2.5997 Acc: 0.6800
Training: 100%|██████████| 160/160 [00:47<00:00,  3.40it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.80it/s]
Epoch 12/30 | Train Loss: 2.2042 Acc: 0.8157 | Val Loss: 2.3435 Acc: 0.7267
Training: 100%|██████████| 160/160 [00:47<00:00,  3.39it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.80it/s]
Epoch 13/30 | Train Loss: 2.0458 Acc: 0.8245 | Val Loss: 2.3134 Acc: 0.7100
Training: 100%|██████████| 160/160 [00:47<00:00,  3.38it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.80it/s]
Epoch 14/30 | Train Loss: 1.8975 Acc: 0.8430 | Val Loss: 2.1997 Acc: 0.7167
Training: 100%|██████████| 160/160 [00:47<00:00,  3.40it/s]
Evaluating: 100%|██████████| 29/29 [00:10<00:00,  2.77it/s]
```
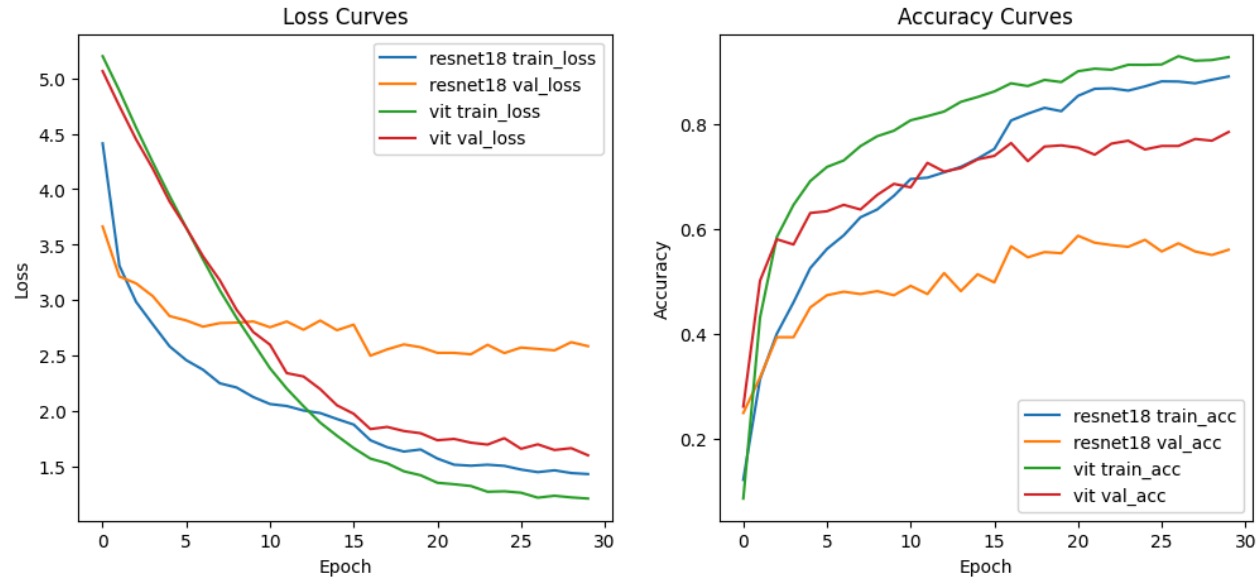

```
# ================================================================================
# 7. Compare Models
# ================================================================================
print("\n=== Model Comparison ===")
comparison_data = {
        "Model": list(test_results.keys()),
        "Test Accuracy": [f"{test_results[m]['acc']:.4f}" for m in test_results],
        "Test Top-5 Accuracy": [f"{test_results[m]['top5_acc']:.4f}" for m in test_results],
        "Macro F1-Score": [f"{test_results[m]['macro_f1']:.4f}" for m in test_results],
        "Total Train Time (s)": [f"{test_results[m]['train_time']:.1f}" for m in test_results]
}
print(pd.DataFrame(comparison_data).to_markdown(index=False))    # Requires import pandas as pd if needed

# Plot combined curves
plt.figure(figsize=(12, 5))
for name in all_history:
        plt.subplot(1, 2, 1)
        plt.plot(all_history[name]["train_loss"], label=f"{name} train_loss")
        plt.plot(all_history[name]["val_loss"], label=f"{name} val_loss")
        plt.title("Loss Curves")
        plt.xlabel("Epoch")
        plt.ylabel("Loss")
        plt.legend()

        plt.subplot(1, 2, 2)
        plt.plot(all_history[name]["train_acc"], label=f"{name} train_acc")
        plt.plot(all_history[name]["val_acc"], label=f"{name} val_acc")
        plt.title("Accuracy Curves")
        plt.xlabel("Epoch")
        plt.ylabel("Accuracy")
        plt.legend()
plt.show()
```

```
Evaluating: 100%|████████████████| 29/29 [00:10<00:00,  2.74it/s]
Epoch 27/30 | Train Loss: 1.2215 Acc: 0.9299 | Val Loss: 1.7018 Acc: 0.7589
Training: 100%|████████████████| 160/160 [00:48<00:00,  3.27it/s]
Evaluating: 100%|████████████████| 29/29 [00:10<00:00,  2.74it/s]
Epoch 28/30 | Train Loss: 1.2386 Acc: 0.9213 | Val Loss: 1.6510 Acc: 0.7722
Training: 100%|████████████████| 160/160 [00:48<00:00,  3.30it/s]
Evaluating: 100%|████████████████| 29/29 [00:10<00:00,  2.79it/s]
```

=== Model Comparison ===

Model	Test Accuracy	Top-5 Accuracy	Macro F1-Score	Total Train Time (s)
resnet18	0.6845	0.8942	0.6827	1225.9
vit	0.8748	0.9789	0.8728	1761.5




```
# ================================================================================
# 8. Plot Confusion Matrices for Both Models
# ================================================================================
print("\n=== Plotting Confusion Matrices ===")

for name in test_results:
        y_true = test_results[name]['labels']      # list or np.array of true labels
        y_pred = test_results[name]['preds']       # list or np.array of predicted labels

        # Compute Confusion Matrice (200x200)
        cm = confusion_matrix(y_true, y_pred)

        # Normalized (row-normalized to 1, easier to see error distribution)
        cm_normalized = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        cm_normalized = np.nan_to_num(cm_normalized)
```