Assignment 2 Understanding transfer learning and fine tuning

In [1]:
```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, Dataset
from torch.utils.data import Dataset
import torch.nn.functional as F
import matplotlib.pyplot as plt
from PIL import Image
from torchvision import transforms
from torch.utils.data import random_split
from torchvision import datasets
import os
import numpy as np
from typing import Literal
from torchvision.models import resnet18, ResNet18_Weights
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, recall_score
from torch.amp import autocast, GradScaler

print(f"[INFO] Torch infos: {torch.__version__}")

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"[INFO] Using device: {device}")
```

```
[INFO] Torch infos: 2.10.0+cu126
[INFO] Using device: cuda
```

We need transform from resnet18 and its weights

In [2]:
```
transform = ResNet18_Weights.DEFAULT.transforms()
```

pick a dataset you can import from

```
from torchvision import datasets
```

Easy picks:

- Food101
- Flowers102
- DTD
- FGVAircraft

Other picks:

```
full_train = datasets.OxfordIIITPet(root="data", split="trainval", download=True, transform=transform)
test_ds    = datasets.OxfordIIITPet(root="data", split="test", download=True, transform=transform)
```

Split the data

In [ ]:
```
# Oxford pet dataset

full_train = datasets.OxfordIIITPet(root="data", split="trainval", download=True, transform=transform)
test_ds    = datasets.OxfordIIITPet(root="data", split="test",     download=True, transform=transform)

# Train/val split
val_ratio = 0.2
val_size = int(len(full_train) * val_ratio)
train_size = len(full_train) - val_size
train_ds, val_ds = random_split(full_train, [train_size, val_size])

print(f"Train size:      {len(train_ds)}")
print(f"Validation size: {len(val_ds)}")
print(f"Test size:       {len(test_ds)}")
```

```
Train size:      2944
Validation size: 736
Test size:       3669
```

load the train, validation and test split

In [ ]:
```
# Configurations
NUM_CLASSES = 37
EPOCHS = 2
PATIENCE = 1
BATCH_SIZE = 64
SCALER = GradScaler()
```

create dataloader handler from the dataset

In [5]:
```
# Trying out num_workers for more efficiency
train_loader = DataLoader(train_ds, batch_size=BATCH_SIZE,num_workers=4, shuffle=True)
val_loader   = DataLoader(val_ds,   batch_size=BATCH_SIZE,num_workers=4, shuffle=False)
test_loader  = DataLoader(test_ds,  batch_size=BATCH_SIZE,num_workers=4, shuffle=False)

print(f"Train batches: {len(train_loader)}")
print(f"Val batches:   {len(val_loader)}")
print(f"Test batches:  {len(test_loader)}")
```

```
Train batches: 46
Val batches:   12
Test batches:  58
```

now create the cnn, use the resnet18 as backbone, and ResNet18_Weights as initial weights.

- create the backbone
- create a classifier
- based on your dataset add the correct number of output classes
- the classifier have to be trainable.

Question 1?

- Why we freeze the backbone? Why not the classifier?

Answer

- We freeze backbone because it was already trained on ImageNet general purpose patterns (edges, textures, shapes). Freezing it means those weights are not updated during training, which:

1. Saves computation
2. Prevents destroying the learned patterns

In [ ]:
```python
# Model for transferleaning From class power point example
class ResNet18Transfer(nn.Module):
    def __init__(self,
                 num_classes: int,
                 freeze_backbone: bool = True,
                 dense_units: list[int] = [256],
                 dropout_probabilities: float = 0.3,
                 weights=ResNet18_Weights.DEFAULT):
        super().__init__()
        self.weights = weights

        # Create a feature extractor
        backbone = resnet18(weights=weights)
        self.features = nn.Sequential(*list(backbone.children())[:-1])
        self.backbone_out = 512  # 512 for ResNet18

        # Freeze the layers
        if freeze_backbone:
            for p in self.features.parameters():
                p.requires_grad = False

        # Classifier
        mlp = []
        cur = self.backbone_out
        for h in dense_units:
            mlp += [
```

```
                nn.Linear(cur, h),
                nn.ReLU(inplace=True),
                nn.Dropout(p=dropout_probabilities),
            ]
            cur = h  # Update current size

        # Add final classifier
        self.classifier = nn.Sequential(*mlp)
        self.final_classifier = nn.Linear(cur, num_classes)

        # Ensure head trainable
        for p in self.classifier.parameters():
            p.requires_grad = True
        for p in self.final_classifier.parameters():
            p.requires_grad = True

    def forward(self, x):
        x = self.features(x)
        x = torch.flatten(x, 1)
        x = self.classifier(x)

        return self.final_classifier(x)

    # Helper to unfreeze in phase2
    def unfreeze_layer4(self):
        # features[7] is layer4 in ResNet18
        for p in self.features[7].parameters():
            p.requires_grad = True

model = ResNet18Transfer(num_classes=NUM_CLASSES, freeze_backbone=True, dropout_probabilities=0.3).to(device)
print(model)
```

```
ResNet18Transfer(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
    (4): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (1): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (5): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
```

```
    (6): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (7): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (8): AdaptiveAvgPool2d(output_size=(1, 1))
  )
```

```
  (classifier): Sequential(
    (0): Linear(in_features=512, out_features=256, bias=True)
    (1): ReLU(inplace=True)
    (2): Dropout(p=0.3, inplace=False)
  )
  (final_classifier): Linear(in_features=256, out_features=37, bias=True)
)
```

add the train evaluation, and predict functions here

In [ ]:
```python
# Training for one epoch
def train_one_epoch(model, loader, criterion, optimizer, scaler):

    model.train()
    total_loss = 0.0
    all_preds, all_labels = [], []

    for images, labels in loader:
        images, labels = images.to(device), labels.to(device)

        optimizer.zero_grad()

        with autocast(device_type="cuda"):
            outputs = model(images)
            loss = criterion(outputs, labels)

        # Trying scaler to better performance
        scaler.scale(loss).backward()
        scaler.step(optimizer)
        scaler.update()

        total_loss += loss.item()
        preds = outputs.argmax(dim=1)
        all_preds.extend(preds.cpu().numpy())
        all_labels.extend(labels.cpu().numpy())

    avg_loss = total_loss / len(loader)
    acc = accuracy_score(all_labels, all_preds)
    return avg_loss, acc
```

```python
# Evaluating function for model
def evaluate(model, loader, criterion, device):

    model.eval()
    total_loss = 0.0
    all_preds, all_labels = [], []

    with torch.no_grad():
        for images, labels in loader:
            images, labels = images.to(device), labels.to(device)

            with autocast(device_type="cuda"):
                outputs = model(images)
                loss = criterion(outputs, labels)

            total_loss += loss.item()
            preds = outputs.argmax(dim=1)
            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    avg_loss = total_loss / len(loader)
    acc = accuracy_score(all_labels, all_preds)
    return avg_loss, acc

# Training function for model, with stopping early
def train(model, train_loader, val_loader, criterion, optimizer, epochs, scaler, patience=PATIENCE):

    train_losses, val_losses = [], []
    train_accs, val_accs = [], []

    best_val_loss = float('inf')
    patience_counter = 0
    best_model_state = None

    for epoch in range(1, epochs + 1):
        train_loss, train_acc = train_one_epoch(model, train_loader, criterion, optimizer, scaler)
        val_loss, val_acc = evaluate(model, val_loader, criterion, device)

        train_losses.append(train_loss)
        val_losses.append(val_loss)
        train_accs.append(train_acc)
```

```
        val_accs.append(val_acc)

        # Tryin early stopping
        if val_loss < best_val_loss:
            best_val_loss = val_loss
            patience_counter = 0
            best_model_state = model.state_dict().copy()
        else:
            patience_counter += 1

        if patience_counter >= patience:
            print(f"\n[EARLY STOP] No improvement for {patience} epochs. Stopping at epoch {epoch}.")
            model.load_state_dict(best_model_state)
            break

        # If results stumble 5 consequtive epochs stop learning
        if epoch % 5 == 0 or epoch == 1:
            print(f"Epoch {epoch:3d}/{epochs} | "
                  f"Train Loss: {train_loss:.4f}, Train Acc: {train_acc:.4f} | "
                  f"Val Loss: {val_loss:.4f}, Val Acc: {val_acc:.4f}")

    return train_losses, val_losses, train_accs, val_accs

# Prediction function for model
def predict(model, loader, device):

    model.eval()
    all_preds, all_labels = [], []

    with torch.no_grad():
        for images, labels in loader:
            images = images.to(device)

            with autocast(device_type="cuda"):
                outputs = model(images)

            preds = outputs.argmax(dim=1)
            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(labels.numpy())

    return np.array(all_preds), np.array(all_labels)
```

Phase 1: Transfer learning

freeze all layers except the classifier.

- train and evaluate the model for 50 epochs
- remember to save val loss and train loss

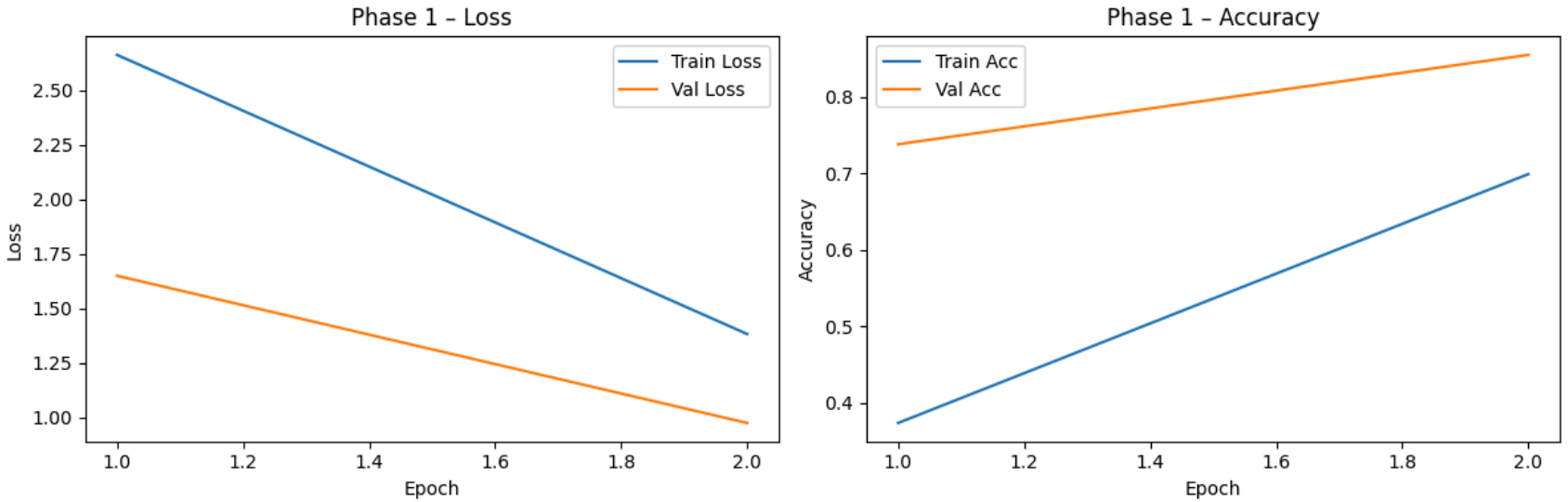
In [ ]:
```
# Freeze backbone parameters
for param in model.features.parameters():
    param.requires_grad = False

# Only the classifier parameters will be updated, because it the new added layer
optimizer = optim.Adam(model.classifier.parameters(), lr=1e-3)
criterion = nn.CrossEntropyLoss()

# Train for 50 epochs using the train() function
phase1_train_losses, phase1_val_losses, phase1_train_accs, phase1_val_accs = train(
    model, train_loader, val_loader, criterion, optimizer, scaler=SCALER, epochs=EPOCHS, patience=PATIENCE
)
```

```
Epoch   1/2 | Train Loss: 2.6623, Train Acc: 0.3733 | Val Loss: 1.6500, Val Acc: 0.7378
```

Plot accuracy and loss

In [9]:
```
epochs_range = range(1, EPOCHS + 1)

fig, axes = plt.subplots(1, 2, figsize=(12, 4))

# Loss curve
axes[0].plot(epochs_range, phase1_train_losses, label="Train Loss")
axes[0].plot(epochs_range, phase1_val_losses,   label="Val Loss")
axes[0].set_title("Phase 1 – Loss")
axes[0].set_xlabel("Epoch")
axes[0].set_ylabel("Loss")
axes[0].legend()
```

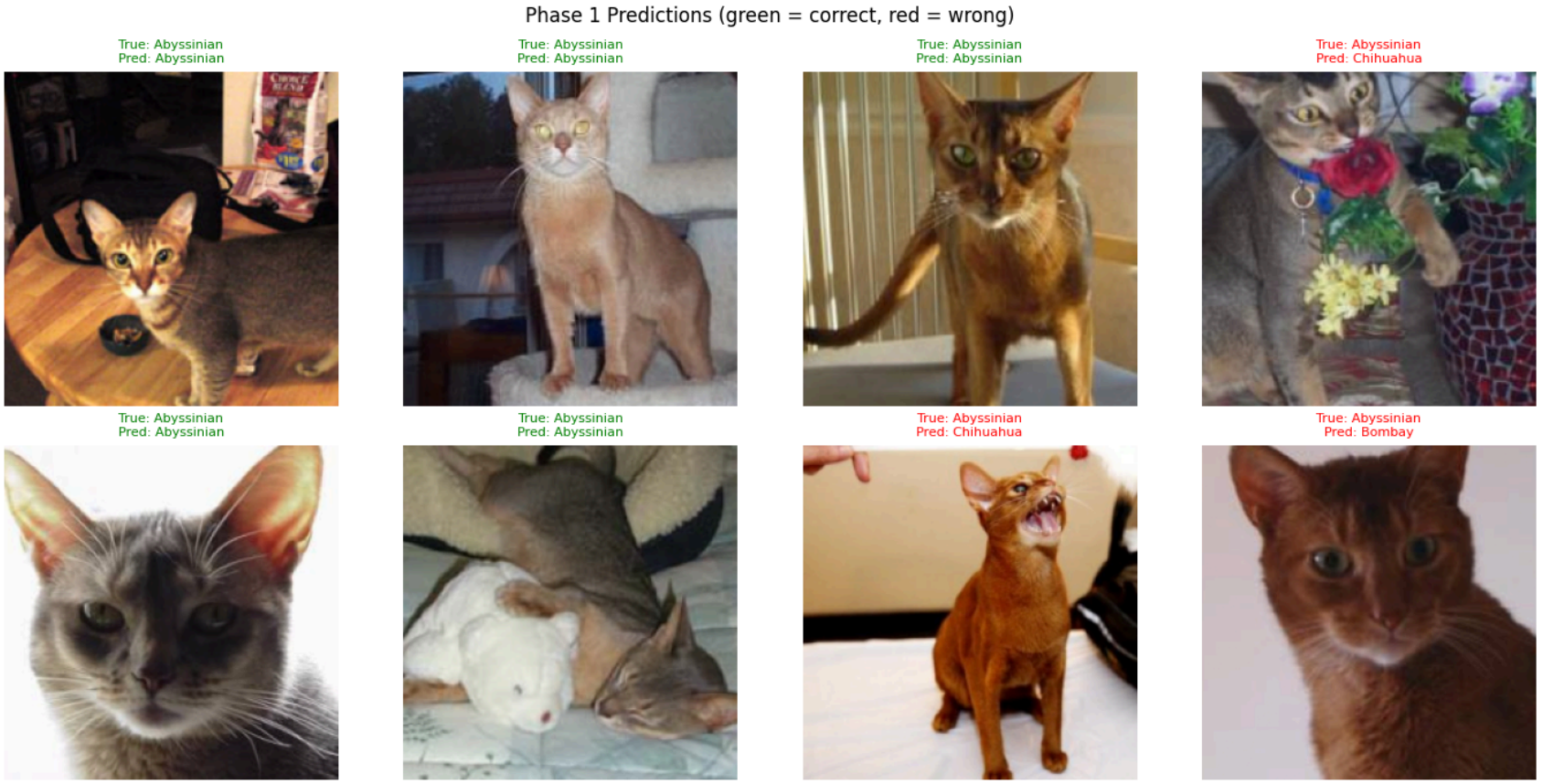
```
# Accuracy curve
axes[1].plot(epochs_range, phase1_train_accs, label="Train Acc")
axes[1].plot(epochs_range, phase1_val_accs,   label="Val Acc")
axes[1].set_title("Phase 1 – Accuracy")
axes[1].set_xlabel("Epoch")
axes[1].set_ylabel("Accuracy")
axes[1].legend()

plt.tight_layout()
plt.show()
```



plot predictions

In [ ]:
```
# Grid of guesses for visualization, same type used in assignment 1
class_names = test_ds.classes  # list of 37 breed names

# Grab one batch from the test loader
images_batch, labels_batch = next(iter(test_loader))
outputs = model(images_batch.to(device))
preds_batch = outputs.argmax(dim=1).cpu()

# ImageNet normalisation used by ResNet – we reverse it for display
mean = torch.tensor([0.485, 0.456, 0.406])
```

```
std  = torch.tensor([0.229, 0.224, 0.225])

fig, axes = plt.subplots(2, 4, figsize=(14, 7))
for i, ax in enumerate(axes.flat):
    img = images_batch[i].permute(1, 2, 0) * std + mean
    img = img.clamp(0, 1).numpy()
    ax.imshow(img)
    true_name = class_names[labels_batch[i]]
    pred_name = class_names[preds_batch[i]]
    color = "green" if labels_batch[i] == preds_batch[i] else "red"
    ax.set_title(f"True: {true_name}\nPred: {pred_name}", color=color, fontsize=8)
    ax.axis("off")

plt.suptitle("Phase 1 Predictions (green = correct, red = wrong)", fontsize=12)
plt.tight_layout()
plt.show()
```



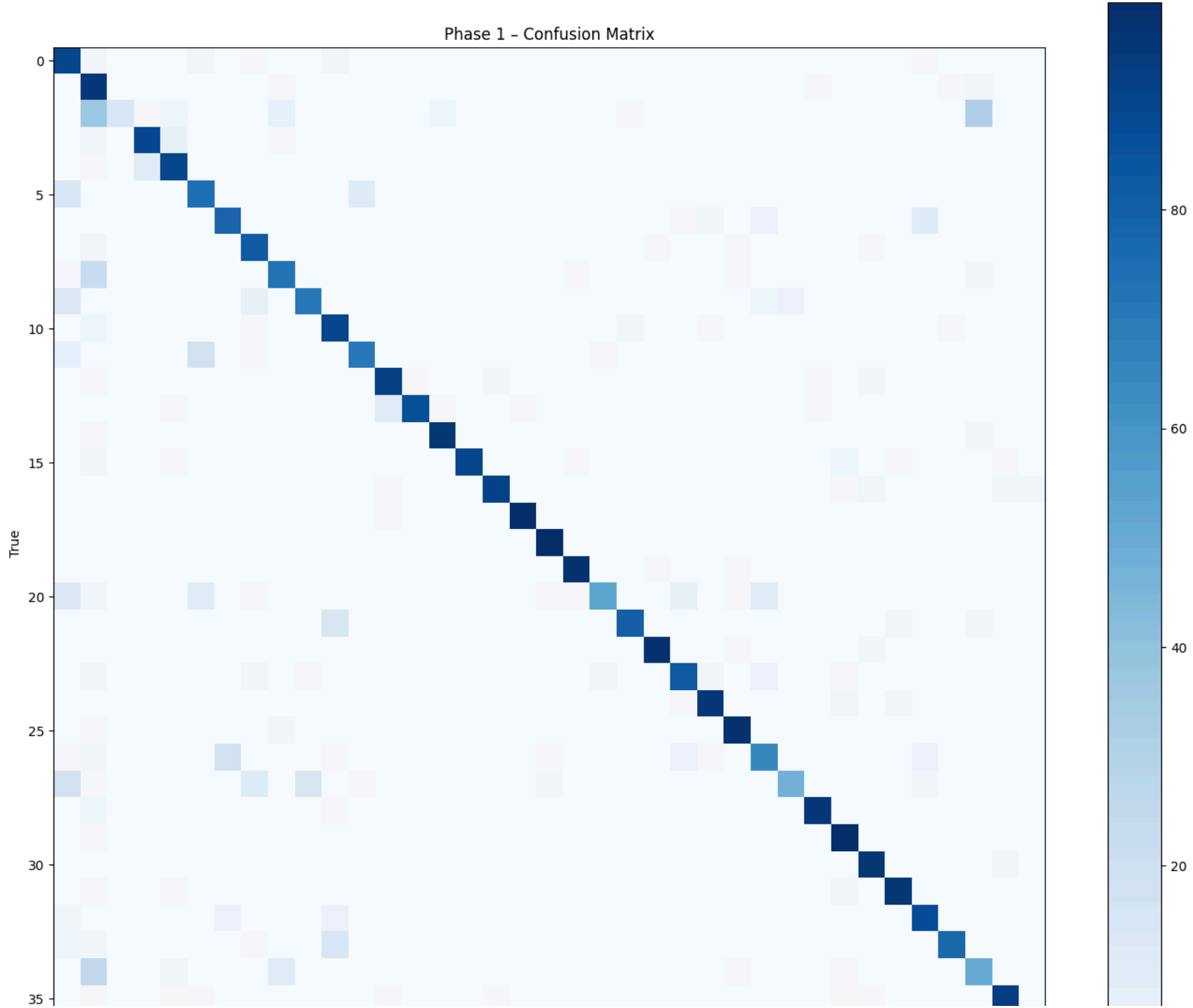
calculate TEST accuracy score

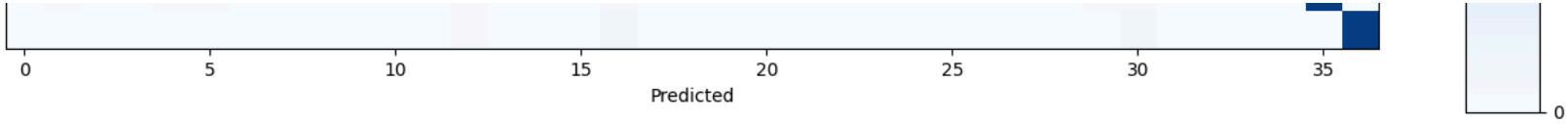
In [13]:
```
phase1_preds, phase1_labels = predict(model, test_loader, device)
phase1_test_acc = accuracy_score(phase1_labels, phase1_preds)
print(f"Phase 1 Test Accuracy: {phase1_test_acc:.4f}")
```

```
Phase 1 Test Accuracy: 0.8367
```

Calculate confusion matrices precision and recall

In [ ]:
```
# Confusion matrix
cm = confusion_matrix(phase1_labels, phase1_preds)

fig, ax = plt.subplots(figsize=(14, 12))
im = ax.imshow(cm, cmap="Blues")
plt.colorbar(im, ax=ax)
ax.set_title("Phase 1 – Confusion Matrix")
ax.set_xlabel("Predicted")
ax.set_ylabel("True")
plt.tight_layout()
plt.show()

# Precision recall matrix (macro average for a single summary number)
precision_macro = precision_score(phase1_labels, phase1_preds, average="macro", zero_division=0)
recall_macro    = recall_score(phase1_labels, phase1_preds,    average="macro", zero_division=0)

print(f"Phase 1 Macro Precision: {precision_macro:.4f}")
print(f"Phase 1 Macro Recall:    {recall_macro:.4f}")
```


Phase 1 – Confusion Matrix
True
0
5
10
15
20
25
30
35
80
60
40
20




```
Phase 1 Macro Precision: 0.8618
Phase 1 Macro Recall:    0.8363
```

Phase 2: Freeze layer 4 - Fine tuning

from the freezed cnn unfreeze the `layer4`.

In [ ]:
```python
# Unfreezing layer4
model.unfreeze_layer4()

# Model overfitted heavily with earlier learning rates:
# Using a lower learning rate for the unfrozen backbone layers to avoid
# overwriting the pretrained features too aggressively
optimizer = optim.Adam([
    {"params": model.features[7].parameters(), "lr": 1e-5},      # layer4
    {"params": model.classifier.parameters(), "lr": 5e-4},       # MLP head
    {"params": model.final_classifier.parameters(), "lr": 5e-4}, # final layer
])

scaler = GradScaler()  # Reset scaler
print("layer4 and classifier are now trainable.")
```

```
layer4 and classifier are now trainable.
```

Train for 50 epochs

In [ ]:
```python
# Train with early stopping
print("\n---Phase 2: Fine-Tuning---")
phase2_train_losses, phase2_val_losses, phase2_train_accs, phase2_val_accs = train(
    model, train_loader, val_loader, criterion, optimizer, scaler=SCALER, epochs=2, patience=PATIENCE
)
```

```
=== Phase 2: Fine-Tuning ===
Epoch   1/2 | Train Loss: 0.8729, Train Acc: 0.7802 | Val Loss: 0.5821, Val Acc: 0.8655
```

Plot curves

In [ ]:
```
fig, axes = plt.subplots(1, 2, figsize=(12, 4))

axes[0].plot(epochs_range, phase2_train_losses, label="Train Loss")
axes[0].plot(epochs_range, phase2_val_losses,   label="Val Loss")
axes[0].set_title("Phase 2 – Loss")
axes[0].set_xlabel("Epoch")
axes[0].set_ylabel("Loss")
axes[0].legend()

axes[1].plot(epochs_range, phase2_train_accs, label="Train Acc")
axes[1].plot(epochs_range, phase2_val_accs,   label="Val Acc")
axes[1].set_title("Phase 2 – Accuracy")
axes[1].set_xlabel("Epoch")
axes[1].set_ylabel("Accuracy")
axes[1].legend()

plt.tight_layout()
plt.show()
```

visualize prediction

In [ ]:
```
# Reuse the same batch from phase 1
outputs = model(images_batch.to(device))
preds_batch = outputs.argmax(dim=1).cpu()

fig, axes = plt.subplots(2, 4, figsize=(14, 7))
for i, ax in enumerate(axes.flat):
    img = images_batch[i].permute(1, 2, 0) * std + mean
    img = img.clamp(0, 1).numpy()
    ax.imshow(img)
    true_name = class_names[labels_batch[i]]
    pred_name = class_names[preds_batch[i]]
    color = "green" if labels_batch[i] == preds_batch[i] else "red"
```

```
    ax.set_title(f"True: {true_name}\nPred: {pred_name}", color=color, fontsize=8)
    ax.axis("off")

plt.suptitle("Phase 2 Predictions (green = correct, red = wrong)", fontsize=12)
plt.tight_layout()
plt.show()
```

Calculate test accuracy score

In [ ]:
```
phase2_preds, phase2_labels = predict(model, test_loader)
phase2_test_acc = accuracy_score(phase2_labels, phase2_preds)
print(f"Phase 1 Test Accuracy: {phase1_test_acc:.4f}")
print(f"Phase 2 Test Accuracy: {phase2_test_acc:.4f}")
print(f"Improvement:           {phase2_test_acc - phase1_test_acc:+.4f}")
```

calculate confusion matrix precision and recall

In [ ]:
```
cm2 = confusion_matrix(phase2_labels, phase2_preds)

fig, ax = plt.subplots(figsize=(14, 12))
im = ax.imshow(cm2, cmap="Blues")
plt.colorbar(im, ax=ax)
ax.set_title("Phase 2 – Confusion Matrix")
ax.set_xlabel("Predicted")
ax.set_ylabel("True")
plt.tight_layout()
plt.show()

precision_macro2 = precision_score(phase2_labels, phase2_preds, average="macro", zero_division=0)
recall_macro2    = recall_score(phase2_labels, phase2_preds,    average="macro", zero_division=0)

print(f"Phase 2 Macro Precision: {precision_macro2:.4f}")
print(f"Phase 2 Macro Recall:    {recall_macro2:.4f}")
```

Question 2 – What is the difference between transfer learning and fine tuning?

Transfer learning In phase1 we used pre-trained model and used its feature extraction layers as they were trained. We only trained an add-on classification layer to have fast results with new data. On other words we "froze" pretrained layers.

Fine tuning In phase2 we fine tuned the layer4 of the pre-trained model to have better performance on the new data we wanter to train it on. Risk is to over train and ruin the models perfomance but this is where fine tuning needs to be done well. Smaller learning rates should result in more delicate learning and keep underlying pre-trained perfomance in tact.

Key takeaway: Transfer learning will get some of the results if the pre-trained model is suitable. Therefore we can use large models without actually training it from scratch. Fine tuning comes handy when we want to have better results. This task was already quite computationally heavy and I had to tune down the model for better computational perfomance.