newBNN12464khalf

July 19, 2025

[1]:
```python
# In[1]:
import torch
import torch.nn as nn
import torchvision
import torchvision.transforms as transforms
from torch.utils.data import DataLoader, random_split
from torch.optim.lr_scheduler import ReduceLROnPlateau
from torch.cuda.amp import GradScaler, autocast
from tqdm.notebook import tqdm  # Use tqdm.notebook for notebooks
import os
import copy
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
import numpy as np
```

[2]:
```python
# In[2]:
class Config:
    # --- Dataset & Hardware ---
    # DATA_DIR = 'path/to/your/soyabean_uav_dataset' # <--- CHANGE THIS
    # DATA_DIR = '/home/dragoon/Downloads/dataset' # <--- CHANGE THIS
    DATA_DIR = '/home/dragoon/Downloads/split' # <--- CHANGE THIS
    # DATA_DIR = '/home/dragoon/Downloads/testset' # <--- CHANGE THIS
    NUM_WORKERS = 4

    # --- Model Architecture ---
    IMG_SIZE = 128
    HIDDEN_LAYERS_CONFIG = [32, 64, 128, 256]
    HIDDEN_SIZE_CLASSIFIER = 512

    # --- Training Hyperparameters ---
    NUM_EPOCHS = 100
    BATCH_SIZE = 16
    LEARNING_RATE = 1e-3

    # --- Early Stopping ---
    EARLY_STOP_PATIENCE = 7
    MIN_LR_TO_START_EARLY_STOPPING = 1e-5
```

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

```
Using device: cuda
```

[3]:
```
# In[3]:
train_transform = transforms.Compose([
    transforms.Resize((Config.IMG_SIZE, Config.IMG_SIZE)),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(10),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.5, 0.5, 0.5], std=[0.5, 0.5, 0.5])
])
val_transform = transforms.Compose([
    transforms.Resize((Config.IMG_SIZE, Config.IMG_SIZE)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.5, 0.5, 0.5], std=[0.5, 0.5, 0.5])
])

try:
    full_dataset = torchvision.datasets.ImageFolder(root=Config.DATA_DIR,␣
 ↪transform=train_transform)
    class_names = full_dataset.classes
    NUM_CLASSES = len(class_names)
    print(f"Successfully detected {NUM_CLASSES} classes: {class_names}")

    train_size = int(0.8 * len(full_dataset))
    val_size = len(full_dataset) - train_size
    train_dataset, val_dataset = random_split(full_dataset, [train_size,␣
 ↪val_size])

    val_dataset.dataset.transform = val_transform

    train_loader = DataLoader(train_dataset, batch_size=Config.BATCH_SIZE,␣
 ↪shuffle=True, num_workers=Config.NUM_WORKERS, pin_memory=True,drop_last=True)
    val_loader = DataLoader(val_dataset, batch_size=Config.BATCH_SIZE,␣
 ↪shuffle=False, num_workers=Config.NUM_WORKERS, pin_memory=True)
except FileNotFoundError:
    print(f"ERROR: Dataset not found at '{Config.DATA_DIR}'. Please check the␣
 ↪path.")
```

```
Successfully detected 4 classes: ['Healthy_Soyabean', 'Soyabean Semilooper and
Caterpillar_Pest_Attack', 'Soyabean_Mosaic', 'Soyabean_Rust']
```

1 In[4]:

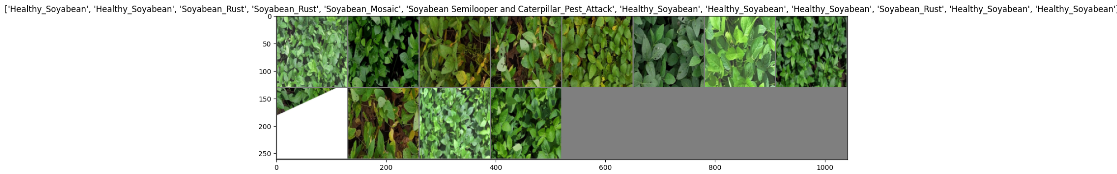
def show_transformed_images(data_loader, class_names, num_images=3): # Un-normalize and display an image def imshow(inp, title=None): inp = inp.numpy().transpose((1, 2, 0)) mean = np.array([0.5, 0.5, 0.5]) std = np.array([0.5, 0.5, 0.5]) inp = std * inp + mean inp = np.clip(inp, 0, 1) plt.imshow(inp) if title is not None: plt.title(title) plt.pause(0.001)

```
# Get a batch of training data
inputs, classes = next(iter(data_loader))

# Make a grid from the batch and show
out = torchvision.utils.make_grid(inputs[:num_images*len(class_names)])

fig, ax = plt.subplots(figsize=(15, 8))
imshow(out, title=[class_names[x] for x in classes[:num_images*len(class_names)]])
```

print("Displaying a sample of transformed images…") show_transformed_images(train_loader, class_names)

[4]:
```
# In[4]:
def show_transformed_images(data_loader, class_names, num_images=3):
    # Un-normalize and display an image
    def imshow(inp, title=None):
        inp = inp.numpy().transpose((1, 2, 0))
        mean = np.array([0.5, 0.5, 0.5])
        std = np.array([0.5, 0.5, 0.5])
        inp = std * inp + mean
        inp = np.clip(inp, 0, 1)
        plt.imshow(inp)
        if title is not None:
            plt.title(title)
        plt.pause(0.001)

    # Get a batch of training data
    inputs, classes = next(iter(data_loader))

    # Make a grid from the batch and show
    out = torchvision.utils.make_grid(inputs[:num_images*len(class_names)])

    fig, ax = plt.subplots(figsize=(15, 8))
    imshow(out, title=[class_names[x] for x in classes[:
 ↪num_images*len(class_names)]])

print("Displaying a sample of transformed images...")
show_transformed_images(train_loader, class_names)
```

```
Displaying a sample of transformed images…
```



[5]:
```python
# In[5]:
class Binarize(torch.autograd.Function):
    @staticmethod
    def forward(ctx, i): return i.sign()
    @staticmethod
    def backward(ctx, grad_output): return grad_output

class BinaryConv2d(nn.Module):
    def __init__(self, in_channels, out_channels, kernel_size, stride=1,␣
 ↪padding=0):
        super().__init__()
        self.conv = nn.Conv2d(in_channels, out_channels, kernel_size, stride,␣
 ↪padding, bias=False)
        self.bn = nn.BatchNorm2d(out_channels)
    def forward(self, x):
        self.conv.weight.data = Binarize.apply(self.conv.weight.data)
        return Binarize.apply(self.bn(self.conv(x)))

class BinaryLinear(nn.Module):
    def __init__(self, in_features, out_features):
        super().__init__()
        self.linear = nn.Linear(in_features, out_features, bias=False)
        self.bn = nn.BatchNorm1d(out_features)
    def forward(self, x):
        self.linear.weight.data = Binarize.apply(self.linear.weight.data)
        return Binarize.apply(self.bn(self.linear(x)))

class BNN(nn.Module):
    def __init__(self, config, num_classes):
        super(BNN, self).__init__()
        layers = []
        in_channels = 3
        for out_channels in config.HIDDEN_LAYERS_CONFIG:
            layers.append(BinaryConv2d(in_channels, out_channels,␣
 ↪kernel_size=3, padding=1))
            layers.append(nn.MaxPool2d(2))
            in_channels = out_channels
        self.features = nn.Sequential(*layers)
        num_pools = len(config.HIDDEN_LAYERS_CONFIG)
```

```
        final_img_size = config.IMG_SIZE // (2**num_pools)
        flat_size = config.HIDDEN_LAYERS_CONFIG[-1] * final_img_size *␣
↪final_img_size
        self.classifier = nn.Sequential(
            BinaryLinear(flat_size, config.HIDDEN_SIZE_CLASSIFIER),
            nn.Linear(config.HIDDEN_SIZE_CLASSIFIER, num_classes)
        )
    def forward(self, x):
        x = self.features(x)
        x = x.view(x.size(0), -1)
        x = self.classifier(x)
        return x
```

[6]:
```
def train_model(model, train_loader, val_loader, config, model_name):
    print(f"\n--- Training {model_name} ---")
    model.to(device)
    criterion = nn.CrossEntropyLoss()
    optimizer = torch.optim.Adam(model.parameters(), lr=config.LEARNING_RATE)
    scheduler = ReduceLROnPlateau(optimizer, 'max', factor=0.2, patience=3)
    scaler = GradScaler()

    best_acc = 0.0
    patience_counter = 0
    history = {'train_loss': [], 'val_loss': [], 'val_acc': []}

    for epoch in range(config.NUM_EPOCHS):
        model.train()
        epoch_train_loss = 0.0
        loop = tqdm(train_loader, desc=f"Epoch {epoch+1}/{config.NUM_EPOCHS}",␣
↪leave=False)
        for images, labels in loop:
            images, labels = images.to(device), labels.to(device)
            optimizer.zero_grad()
            with autocast():
                outputs = model(images)
                loss = criterion(outputs, labels)
            scaler.scale(loss).backward()
            scaler.step(optimizer)
            scaler.update()
            epoch_train_loss += loss.item()
            loop.set_postfix(loss=loss.item())

        val_loss, val_acc = evaluate_model(model, val_loader, criterion)
        history['train_loss'].append(epoch_train_loss / len(train_loader))
        history['val_loss'].append(val_loss)
        history['val_acc'].append(val_acc)
```

```
        current_lr = optimizer.param_groups[0]['lr']
        print(f"Epoch {epoch+1}/{config.NUM_EPOCHS} -> Val Loss: {val_loss:.4f}␣
↪| Val Acc: {val_acc:.2f}% | LR: {current_lr:.1e}")

        scheduler.step(val_acc)

        if val_acc > best_acc:
            best_acc, patience_counter = val_acc, 0
            torch.save(model.state_dict(), f"{model_name}_best.pt")
            print(f"  -> New best model saved with accuracy: {best_acc:.2f}%")
        else:
            if current_lr < config.MIN_LR_TO_START_EARLY_STOPPING:
                patience_counter += 1
                print(f"  -> No improvement. Patience: {patience_counter}/
↪{config.EARLY_STOP_PATIENCE}")
        if patience_counter >= config.EARLY_STOP_PATIENCE:
            print("\n*** Early stopping triggered ***")
            break

    print(f"Finished training. Best Val Acc: {best_acc:.2f}%")
    model.load_state_dict(torch.load(f"{model_name}_best.pt"))
    return model, history

def evaluate_model(model, data_loader, criterion):
    model.eval()
    model.to(device)
    correct, total, running_loss = 0, 0, 0.0
    with torch.no_grad():
        for images, labels in data_loader:
            images, labels = images.to(device), labels.to(device)
            with autocast():
                outputs = model(images)
                loss = criterion(outputs, labels)
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()
            running_loss += loss.item() * images.size(0)
    accuracy = 100 * correct / total
    avg_loss = running_loss / len(data_loader.dataset)
    return avg_loss, accuracy
```

[7]:

```
# In[7]:
def plot_curves(history, model_name):
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(18, 6))
    ax1.plot(history['train_loss'], label='Training Loss')
    ax1.plot(history['val_loss'], label='Validation Loss')
    ax1.set_title(f'{model_name} - Loss Curves')
```

```
    ax1.set_xlabel('Epochs'); ax1.set_ylabel('Loss'); ax1.legend()
    ax2.plot(history['val_acc'], label='Validation Accuracy', color='green')
    ax2.set_title(f'{model_name} - Accuracy Curve')
    ax2.set_xlabel('Epochs'); ax2.set_ylabel('Accuracy (%)'); ax2.legend()
    plt.tight_layout()
    plt.savefig(f"{model_name}_performance_curves.png")
    print(f"Performance curves saved to {model_name}_performance_curves.png")
    plt.show()

def plot_confusion_matrix(model, data_loader, class_names, model_name):
    model.eval(); model.to(device)
    all_preds, all_labels = [], []
    with torch.no_grad():
        for images, labels in data_loader:
            images, labels = images.to(device), labels.to(device)
            with autocast():
                outputs = model(images)
            _, preds = torch.max(outputs, 1)
            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    cm = confusion_matrix(all_labels, all_preds)
    plt.figure(figsize=(10, 8))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_names,␣
 ↪yticklabels=class_names)
    plt.title(f'{model_name} - Confusion Matrix')
    plt.xlabel('Predicted Label'); plt.ylabel('True Label')
    plt.savefig(f"{model_name}_confusion_matrix.png")
    print(f"Confusion matrix saved to {model_name}_confusion_matrix.png")
    plt.show()

def get_model_size_mb(model):
    torch.save(model.state_dict(), "temp.p")
    size_mb = os.path.getsize("temp.p") / 1e6
    os.remove("temp.p")
    return size_mb
```

[ ]:
```
# In[8]:
bnn_model = BNN(config=Config, num_classes=NUM_CLASSES)
trained_bnn, history = train_model(bnn_model, train_loader, val_loader, Config,␣
 ↪"BNN")

# --- Generate Plots ---
plot_curves(history, "BNN")
plot_confusion_matrix(trained_bnn, val_loader, class_names, "BNN")

print("\n\n--- FINAL BNN RESULTS ---")
```

```python
print("="*25)
_, final_accuracy = evaluate_model(trained_bnn, val_loader, nn.
↪CrossEntropyLoss())
model_size = get_model_size_mb(trained_bnn)
print(f"BNN Final Validation Accuracy: {final_accuracy:.2f}%")
print(f"BNN Final Model Size: {model_size:.2f} MB")
print("="*25)
```

```
--- Training BNN ---

/tmp/ipykernel_12894/3243372250.py:7: FutureWarning:
`torch.cuda.amp.GradScaler(args...)` is deprecated. Please use
`torch.amp.GradScaler('cuda', args...)` instead.
  scaler = GradScaler()

Epoch 1/100:   0%|          | 0/3200 [00:00<?, ?it/s]

/tmp/ipykernel_12894/3243372250.py:20: FutureWarning:
`torch.cuda.amp.autocast(args...)` is deprecated. Please use
`torch.amp.autocast('cuda', args...)` instead.
  with autocast():
/tmp/ipykernel_12894/3243372250.py:62: FutureWarning:
`torch.cuda.amp.autocast(args...)` is deprecated. Please use
`torch.amp.autocast('cuda', args...)` instead.
  with autocast():

Epoch 1/100 -> Val Loss: 0.6843 | Val Acc: 71.45% | LR: 1.0e-03
  -> New best model saved with accuracy: 71.45%

Epoch 2/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 2/100 -> Val Loss: 0.7315 | Val Acc: 69.45% | LR: 1.0e-03

Epoch 3/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 3/100 -> Val Loss: 0.6695 | Val Acc: 72.00% | LR: 1.0e-03
  -> New best model saved with accuracy: 72.00%

Epoch 4/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 4/100 -> Val Loss: 0.6946 | Val Acc: 70.59% | LR: 1.0e-03

Epoch 5/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 5/100 -> Val Loss: 0.6867 | Val Acc: 71.59% | LR: 1.0e-03

Epoch 6/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 6/100 -> Val Loss: 0.6499 | Val Acc: 73.12% | LR: 1.0e-03
  -> New best model saved with accuracy: 73.12%

Epoch 7/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 7/100 -> Val Loss: 0.6577 | Val Acc: 73.76% | LR: 1.0e-03
  -> New best model saved with accuracy: 73.76%
```

```
Epoch 8/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 8/100 -> Val Loss: 0.6943 | Val Acc: 71.76% | LR: 1.0e-03
Epoch 9/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 9/100 -> Val Loss: 0.6685 | Val Acc: 72.69% | LR: 1.0e-03
Epoch 10/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 10/100 -> Val Loss: 0.6847 | Val Acc: 71.20% | LR: 1.0e-03
Epoch 11/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 11/100 -> Val Loss: 0.6161 | Val Acc: 74.20% | LR: 1.0e-03
  -> New best model saved with accuracy: 74.20%
Epoch 12/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 12/100 -> Val Loss: 0.6018 | Val Acc: 74.59% | LR: 1.0e-03
  -> New best model saved with accuracy: 74.59%
Epoch 13/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 13/100 -> Val Loss: 0.6712 | Val Acc: 70.85% | LR: 1.0e-03
Epoch 14/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 14/100 -> Val Loss: 0.6497 | Val Acc: 72.02% | LR: 1.0e-03
Epoch 15/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 15/100 -> Val Loss: 0.6335 | Val Acc: 73.84% | LR: 1.0e-03
Epoch 16/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 16/100 -> Val Loss: 0.6483 | Val Acc: 73.09% | LR: 1.0e-03
Epoch 17/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 17/100 -> Val Loss: 0.5974 | Val Acc: 75.71% | LR: 2.0e-04
  -> New best model saved with accuracy: 75.71%
Epoch 18/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 18/100 -> Val Loss: 0.5657 | Val Acc: 77.04% | LR: 2.0e-04
  -> New best model saved with accuracy: 77.04%
Epoch 19/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 19/100 -> Val Loss: 0.6790 | Val Acc: 70.26% | LR: 2.0e-04
Epoch 20/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 20/100 -> Val Loss: 0.6213 | Val Acc: 74.69% | LR: 2.0e-04
Epoch 21/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 21/100 -> Val Loss: 0.5755 | Val Acc: 76.23% | LR: 2.0e-04
Epoch 22/100:   0%|          | 0/3200 [00:00<?, ?it/s]
```

```
Epoch 22/100 -> Val Loss: 0.6492 | Val Acc: 73.15% | LR: 2.0e-04
Epoch 23/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 23/100 -> Val Loss: 0.5984 | Val Acc: 75.87% | LR: 4.0e-05
Epoch 24/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 24/100 -> Val Loss: 0.5800 | Val Acc: 77.00% | LR: 4.0e-05
Epoch 25/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 25/100 -> Val Loss: 0.6501 | Val Acc: 72.70% | LR: 4.0e-05
Epoch 26/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 26/100 -> Val Loss: 0.6749 | Val Acc: 72.89% | LR: 4.0e-05
Epoch 27/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 27/100 -> Val Loss: 0.5938 | Val Acc: 76.10% | LR: 8.0e-06
  -> No improvement. Patience: 1/7
Epoch 28/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 28/100 -> Val Loss: 0.5785 | Val Acc: 76.80% | LR: 8.0e-06
  -> No improvement. Patience: 2/7
Epoch 29/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 29/100 -> Val Loss: 0.5666 | Val Acc: 77.53% | LR: 8.0e-06
  -> New best model saved with accuracy: 77.53%
Epoch 30/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 30/100 -> Val Loss: 0.6281 | Val Acc: 75.38% | LR: 8.0e-06
  -> No improvement. Patience: 1/7
Epoch 31/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 31/100 -> Val Loss: 0.6117 | Val Acc: 75.66% | LR: 8.0e-06
  -> No improvement. Patience: 2/7
Epoch 32/100:   0%|          | 0/3200 [00:00<?, ?it/s]
Epoch 32/100 -> Val Loss: 0.5875 | Val Acc: 76.44% | LR: 8.0e-06
  -> No improvement. Patience: 3/7
Epoch 33/100:   0%|          | 0/3200 [00:00<?, ?it/s]
```