newBNN64k74%

July 19, 2025

[72]:
```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
```

[73]:
```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
    # 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
    # BATCH_SIZE = 4
    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
```

[74]:

```
# 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)
    print(f"Found {len(full_dataset)} images in total.")
    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.")
```

```
Found 64000 images in total.
Successfully detected 4 classes: ['Healthy_Soyabean', 'Soyabean Semilooper and
Caterpillar_Pest_Attack', 'Soyabean_Mosaic', 'Soyabean_Rust']
```

1 In[4]:

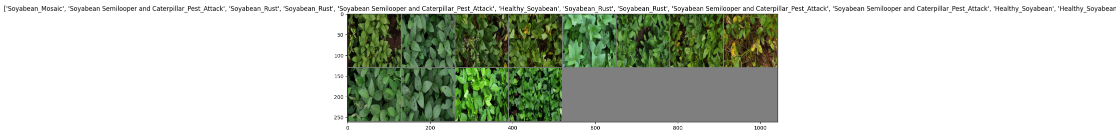
def show_transformed_images(data_loader, class_names, num_images=3): # Un-normalize and display an image def imshow(inp, title=None): inp = inp.numpy().transpose((1, 2, 0)) mean = np.array([0.5, 0.5, 0.5]) std = np.array([0.5, 0.5, 0.5]) inp = std * inp + mean inp = np.clip(inp, 0, 1) plt.imshow(inp) 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)

[75]:
```
# 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…
```



[76]:
```
# 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
```

[77]:
```
import time
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)
    # Added verbose=True to see when LR changes
    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': [], 'epoch_time':␣
↪[]}

    for epoch in range(config.NUM_EPOCHS):
        start_time = time.time() # Start timer at the beginning of the epoch
        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() * images.size(0)
            loop.set_postfix(loss=loss.item())

        val_loss, val_acc = evaluate_model(model, val_loader, criterion)
```

```python
        history['train_loss'].append(epoch_train_loss / len(train_loader.dataset))
        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)

        # --- FIXED: Record epoch time inside the loop ---
        end_time = time.time()
        history['epoch_time'].append(end_time - start_time)

        if val_acc > best_acc:
            best_acc, patience_counter = val_acc, 0
            # --- FIXED: Use the 'model_name' parameter for saving ---
            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}%")
    # --- FIXED: Load the correctly named best model ---
    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
```

[78]:

```
# In[7]:

from datetime import datetime
import pytz

# Define the IST timezone
ist_timezone = pytz.timezone('Asia/Kolkata')

# Get the current time in IST
current_ist_time = datetime.now(ist_timezone)

# Print the current IST time
print("Current IST Time:", current_ist_time.strftime("%Y-%m-%d %H:%M:%S %Z%z"))
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{current_ist_time}.png")
    print(f"Confusion matrix saved to␣
↪{model_name}_confusion_matrix{current_ist_time}.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
```

```
Current IST Time: 2025-07-19 08:07:05 IST+0530
```

[79]:

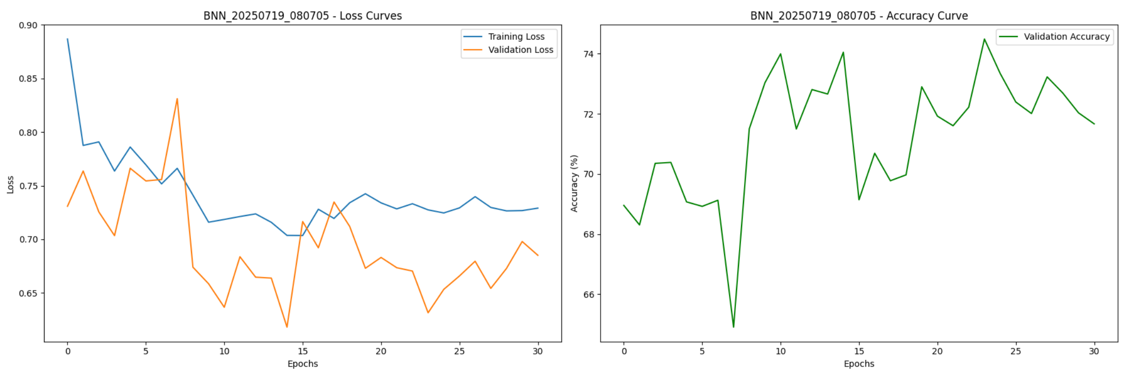
```
# In[8]:
run_timestamp = datetime.now(ist_timezone).strftime("%Y%m%d_%H%M%S")
model_name = f"BNN_{run_timestamp}"
bnn_model = BNN(config=Config, num_classes=NUM_CLASSES)
trained_bnn, history = train_model(bnn_model, train_loader, val_loader, Config,␣
↪model_name)
plot_curves(history, model_name)
plot_confusion_matrix(trained_bnn, val_loader, class_names, model_name)

print("\n\n--- FINAL BNN RESULTS ---")
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_20250719_080705 ---

/tmp/ipykernel_5120/2873454332.py:9: 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_5120/2873454332.py:23: FutureWarning:
`torch.cuda.amp.autocast(args…)` is deprecated. Please use
`torch.amp.autocast('cuda', args…)` instead.
  with autocast():
```

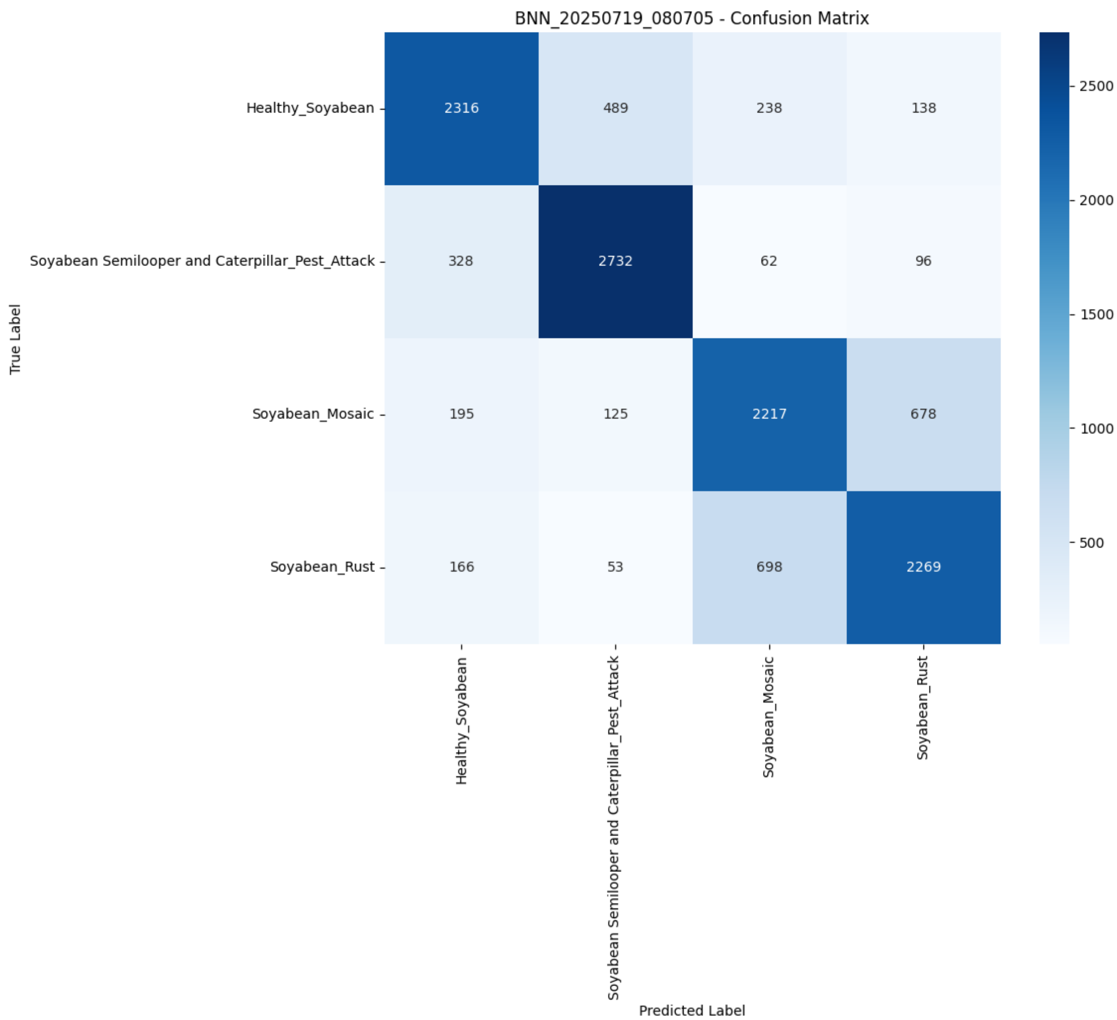
```
/tmp/ipykernel_5120/2873454332.py:71: FutureWarning:
`torch.cuda.amp.autocast(args...)` is deprecated. Please use
`torch.amp.autocast('cuda', args...)` instead.
  with autocast():

Epoch 1/100 -> Val Loss: 0.7308 | Val Acc: 68.95% | LR: 1.0e-03
  -> New best model saved with accuracy: 68.95%

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

Epoch 2/100 -> Val Loss: 0.7637 | Val Acc: 68.30% | LR: 1.0e-03

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

Epoch 3/100 -> Val Loss: 0.7255 | Val Acc: 70.35% | LR: 1.0e-03
  -> New best model saved with accuracy: 70.35%

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

Epoch 4/100 -> Val Loss: 0.7034 | Val Acc: 70.38% | LR: 1.0e-03
  -> New best model saved with accuracy: 70.38%

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

Epoch 5/100 -> Val Loss: 0.7662 | Val Acc: 69.07% | LR: 1.0e-03

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

Epoch 6/100 -> Val Loss: 0.7544 | Val Acc: 68.92% | LR: 1.0e-03

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

Epoch 7/100 -> Val Loss: 0.7557 | Val Acc: 69.12% | LR: 1.0e-03

Epoch 8/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 8/100 -> Val Loss: 0.8312 | Val Acc: 64.91% | LR: 1.0e-03

Epoch 9/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 9/100 -> Val Loss: 0.6740 | Val Acc: 71.50% | LR: 2.0e-04
  -> New best model saved with accuracy: 71.50%

Epoch 10/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 10/100 -> Val Loss: 0.6585 | Val Acc: 73.03% | LR: 2.0e-04
  -> New best model saved with accuracy: 73.03%

Epoch 11/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 11/100 -> Val Loss: 0.6366 | Val Acc: 73.99% | LR: 2.0e-04
  -> New best model saved with accuracy: 73.99%

Epoch 12/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 12/100 -> Val Loss: 0.6837 | Val Acc: 71.49% | LR: 2.0e-04

Epoch 13/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 13/100 -> Val Loss: 0.6646 | Val Acc: 72.80% | LR: 2.0e-04
```

```
Epoch 14/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 14/100 -> Val Loss: 0.6638 | Val Acc: 72.66% | LR: 2.0e-04

Epoch 15/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 15/100 -> Val Loss: 0.6180 | Val Acc: 74.05% | LR: 2.0e-04
  -> New best model saved with accuracy: 74.05%

Epoch 16/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 16/100 -> Val Loss: 0.7166 | Val Acc: 69.14% | LR: 2.0e-04

Epoch 17/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 17/100 -> Val Loss: 0.6920 | Val Acc: 70.69% | LR: 2.0e-04

Epoch 18/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 18/100 -> Val Loss: 0.7348 | Val Acc: 69.77% | LR: 2.0e-04

Epoch 19/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 19/100 -> Val Loss: 0.7120 | Val Acc: 69.97% | LR: 2.0e-04

Epoch 20/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 20/100 -> Val Loss: 0.6729 | Val Acc: 72.90% | LR: 4.0e-05

Epoch 21/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 21/100 -> Val Loss: 0.6830 | Val Acc: 71.92% | LR: 4.0e-05

Epoch 22/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 22/100 -> Val Loss: 0.6735 | Val Acc: 71.60% | LR: 4.0e-05

Epoch 23/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 23/100 -> Val Loss: 0.6704 | Val Acc: 72.22% | LR: 4.0e-05

Epoch 24/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 24/100 -> Val Loss: 0.6314 | Val Acc: 74.48% | LR: 8.0e-06
  -> New best model saved with accuracy: 74.48%

Epoch 25/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 25/100 -> Val Loss: 0.6533 | Val Acc: 73.34% | LR: 8.0e-06
  -> No improvement. Patience: 1/7

Epoch 26/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 26/100 -> Val Loss: 0.6658 | Val Acc: 72.39% | LR: 8.0e-06
  -> No improvement. Patience: 2/7

Epoch 27/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 27/100 -> Val Loss: 0.6795 | Val Acc: 72.01% | LR: 8.0e-06
  -> No improvement. Patience: 3/7

Epoch 28/100:   0%|          | 0/3200 [00:00<?, ?it/s]
```

```
Epoch 28/100 -> Val Loss: 0.6542 | Val Acc: 73.23% | LR: 8.0e-06
  -> No improvement. Patience: 4/7

Epoch 29/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 29/100 -> Val Loss: 0.6728 | Val Acc: 72.69% | LR: 1.6e-06
  -> No improvement. Patience: 5/7

Epoch 30/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 30/100 -> Val Loss: 0.6979 | Val Acc: 72.03% | LR: 1.6e-06
  -> No improvement. Patience: 6/7

Epoch 31/100:   0%|          | 0/3200 [00:00<?, ?it/s]

Epoch 31/100 -> Val Loss: 0.6851 | Val Acc: 71.66% | LR: 1.6e-06
  -> No improvement. Patience: 7/7

*** Early stopping triggered ***
Finished training. Best Val Acc: 74.48%
Performance curves saved to BNN_20250719_080705_performance_curves.png
```




```
/tmp/ipykernel_5120/1421376743.py:34: FutureWarning:
`torch.cuda.amp.autocast(args...)` is deprecated. Please use
`torch.amp.autocast('cuda', args...)` instead.
  with autocast():

Confusion matrix saved to BNN_20250719_080705_confusion_matrix2025-07-19
08:07:05.882075+05:30.png
```




```
--- FINAL BNN RESULTS ---
=========================

/tmp/ipykernel_5120/2873454332.py:71: FutureWarning:
`torch.cuda.amp.autocast(args...)` is deprecated. Please use
`torch.amp.autocast('cuda', args...)` instead.
  with autocast():

BNN Final Validation Accuracy: 74.48%
BNN Final Model Size: 35.14 MB
=========================
```

[80]:

```
# In[9]:
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
```

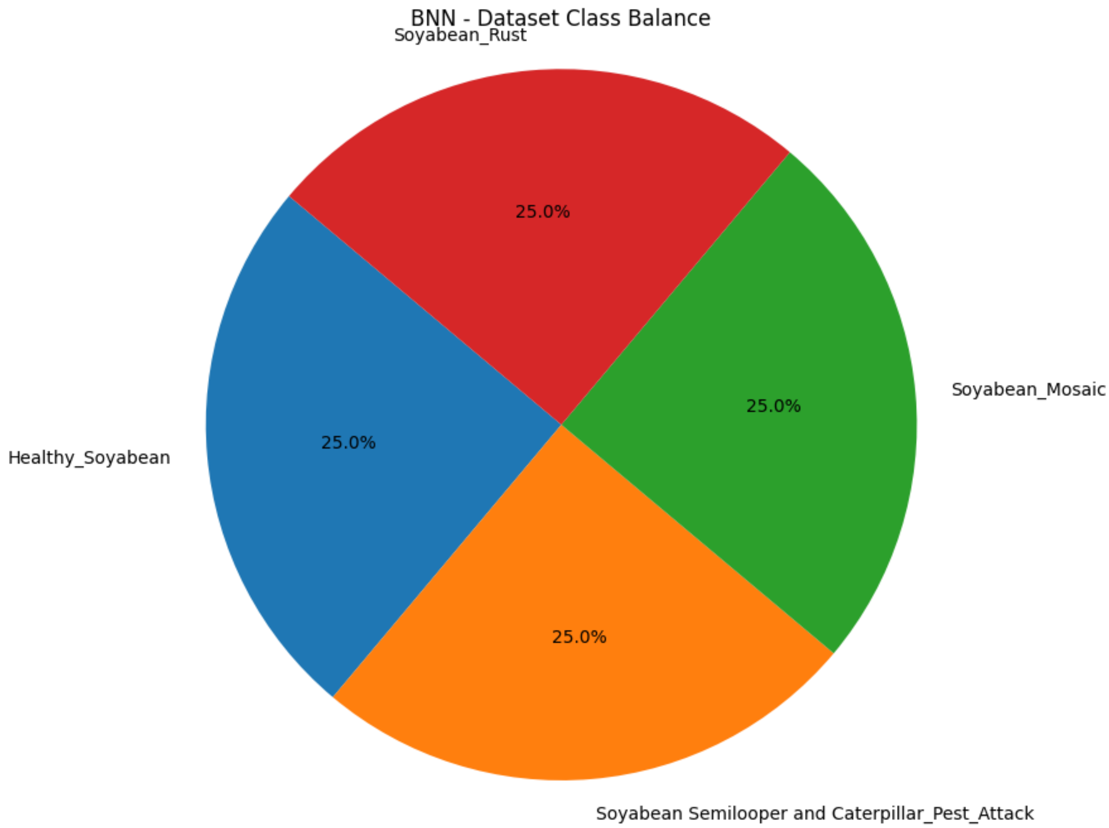
```python
from itertools import cycle
import collections

def plot_roc_auc_curves(model, data_loader, class_names, model_name):
    model.eval()
    model.to(device)
    y_true = []
    y_scores = []

    with torch.no_grad():
        for images, labels in data_loader:
            images, labels = images.to(device), labels.to(device)
            with autocast():
                outputs = model(images)
                # Use softmax to get probabilities
                scores = torch.softmax(outputs, dim=1)
            y_scores.extend(scores.cpu().numpy())
            y_true.extend(labels.cpu().numpy())

    # Binarize the labels for multi-class ROC
    y_true_binarized = label_binarize(y_true, classes=range(len(class_names)))
    y_scores = np.array(y_scores)

    fpr = dict()
    tpr = dict()
    roc_auc = dict()

    for i in range(len(class_names)):
        fpr[i], tpr[i], _ = roc_curve(y_true_binarized[:, i], y_scores[:, i])
        roc_auc[i] = auc(fpr[i], tpr[i])

    plt.figure(figsize=(10, 8))
    colors = cycle(['aqua', 'darkorange', 'cornflowerblue', 'green', 'red'])
    for i, color in zip(range(len(class_names)), colors):
        plt.plot(fpr[i], tpr[i], color=color, lw=2,
                 label=f'ROC curve of class {class_names[i]} (area =␣
↪{roc_auc[i]:0.2f})')

    plt.plot([0, 1], [0, 1], 'k--', lw=2)
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'{model_name} - Multi-Class ROC/AUC Curves')
    plt.legend(loc="lower right")
    plt.savefig(f"{model_name}_roc_auc_curves.png")
    print(f"ROC/AUC curves saved to {model_name}_roc_auc_curves.png")
```

```python
    plt.show()

def plot_epoch_times(history, model_name):
    plt.figure(figsize=(12, 6))
    plt.bar(range(1, len(history['epoch_time']) + 1), history['epoch_time'],␣
↪color='teal')
    plt.title(f'{model_name} - Time Taken Per Epoch')
    plt.xlabel('Epoch')
    plt.ylabel('Time (seconds)')
    plt.savefig(f"{model_name}_epoch_times.png")
    print(f"Epoch times chart saved to {model_name}_epoch_times.png")
    plt.show()

def plot_class_balance(dataset, class_names, model_name):
    class_counts = collections.Counter(dataset.targets)
    counts = [class_counts[i] for i in range(len(class_names))]

    plt.figure(figsize=(8, 8))
    plt.pie(counts, labels=class_names, autopct='%1.1f%%', startangle=140)
    plt.title(f'{model_name} - Dataset Class Balance')
    plt.axis('equal')
    plt.savefig(f"{model_name}_class_balance.png")
    print(f"Class balance pie chart saved to {model_name}_class_balance.png")
    plt.show()

def save_report(config, full_dataset, train_dataset, val_dataset, history,␣
↪model_name):
    with open(f"{model_name}_report.txt", "w") as f:
        f.write("="*30 + "\n")
        f.write(f"Training Report for: {model_name}\n")
        f.write("="*30 + "\n\n")

        f.write("## Configuration ##\n")
        for key, value in vars(config).items():
            if not key.startswith('__'):
                f.write(f"{key}: {value}\n")

        f.write("\n## Dataset Information ##\n")
        f.write(f"Total Images: {len(full_dataset)}\n")
        f.write(f"Training Images: {len(train_dataset)}\n")
        f.write(f"Validation Images: {len(val_dataset)}\n\n")

        f.write("Class Distribution:\n")
        class_counts = collections.Counter(full_dataset.targets)
        for i, class_name in enumerate(full_dataset.classes):
            f.write(f"  - {class_name}: {class_counts[i]} images\n")
```

```
        f.write("\n## Training Summary ##\n")
        total_training_time = sum(history['epoch_time'])
        f.write(f"Total Training Time: {total_training_time:.2f} seconds\n")
        f.write(f"Number of Epochs Trained: {len(history['epoch_time'])}\n")

    print(f"Configuration and dataset report saved to {model_name}_report.txt")
```

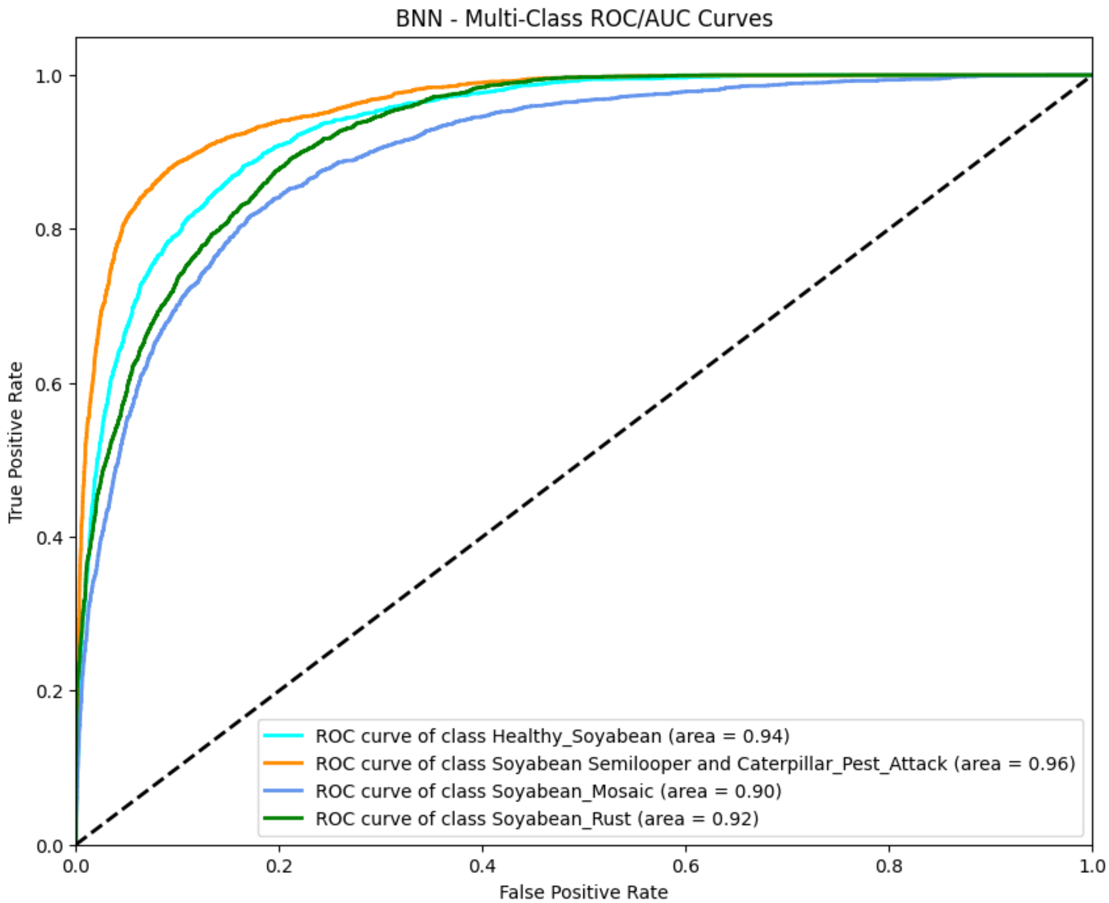
[81]:
```
# In[10]:
# --- Generate All Plots and Reports ---

# Call the functions defined in the previous cell
plot_class_balance(full_dataset, class_names, "BNN")
plot_roc_auc_curves(trained_bnn, val_loader, class_names, "BNN")
plot_epoch_times(history, "BNN")

# Save the final configuration and dataset summary report
save_report(Config, full_dataset, train_dataset, val_dataset, history, "BNN")


# --- Print Final Summary ---
print("\n\n--- FINAL BNN RESULTS ---")
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)
```

```
Class balance pie chart saved to BNN_class_balance.png
```

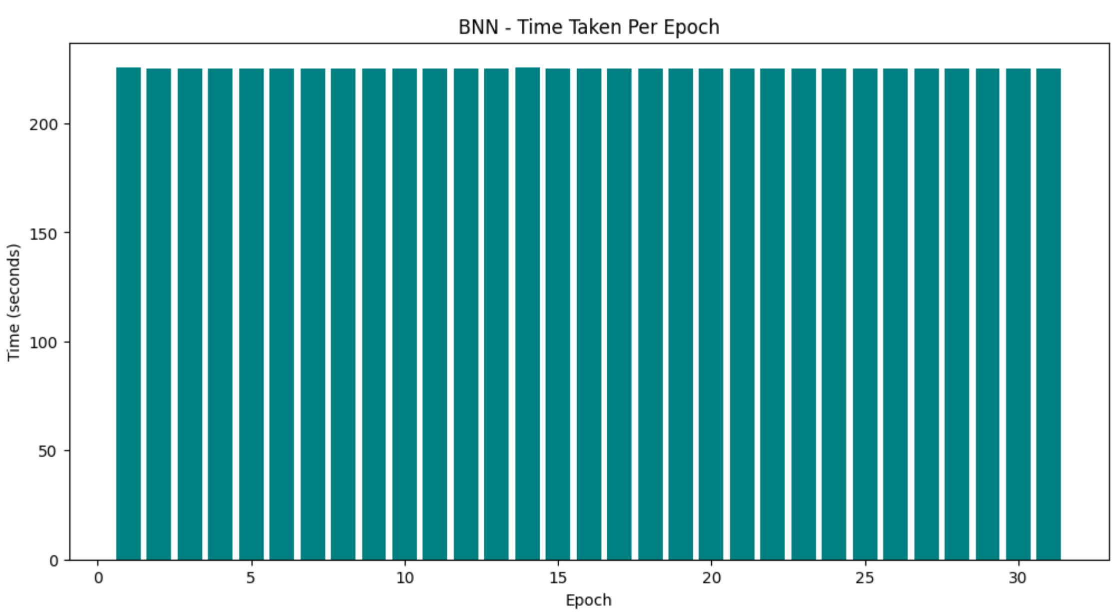



```
/tmp/ipykernel_5120/3905505421.py:16: FutureWarning:
`torch.cuda.amp.autocast(args...)` is deprecated. Please use
`torch.amp.autocast('cuda', args...)` instead.
  with autocast():
```

```
ROC/AUC curves saved to BNN_roc_auc_curves.png
```




```
Epoch times chart saved to BNN_epoch_times.png
```



```
Configuration and dataset report saved to BNN_report.txt


--- FINAL BNN RESULTS ---
=========================

/tmp/ipykernel_5120/2873454332.py:71: FutureWarning:
`torch.cuda.amp.autocast(args…)` is deprecated. Please use
`torch.amp.autocast('cuda', args…)` instead.
  with autocast():

BNN Final Validation Accuracy: 74.48%
BNN Final Model Size: 35.14 MB
=========================
```