BNN224

June 29, 2025

1 Binary Neural Network (BNN) for Plant Disease Classification

This notebook implements a Binary Neural Network using PyTorch for multiclass plant disease classification. The BNN uses binary weights and activations to reduce model size and computational requirements while maintaining reasonable accuracy.

1.1 Features:

- Binary weights and activations using sign function
- Processes 224x224 RGB images (3×224×224 input)
- One hidden layer with binary weights
- Multiclass output with softmax activation
- CrossEntropyLoss for training

[4]:
```python
# Import Required Libraries
%pip install torch torchvision matplotlib numpy pandas seaborn scikit-learn
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import DataLoader, TensorDataset
import numpy as np
import matplotlib.pyplot as plt
from torchvision import transforms
import random

# Set random seeds for reproducibility
torch.manual_seed(42)
np.random.seed(42)
random.seed(42)

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

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Requirement already satisfied: torch in ./.venv/lib/python3.11/site-packages
(2.7.1)
Requirement already satisfied: torchvision in ./.venv/lib/python3.11/site-
packages (0.22.1)
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Requirement already satisfied: six>=1.5 in ./.venv/lib/python3.11/site-packages
(from python-dateutil>=2.7->matplotlib) (1.17.0)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in
./.venv/lib/python3.11/site-packages (from sympy>=1.13.3->torch) (1.3.0)
Requirement already satisfied: MarkupSafe>=2.0 in ./.venv/lib/python3.11/site-
packages (from jinja2->torch) (3.0.2)
Note: you may need to restart the kernel to use updated packages.
Using device: cuda
```

[5]:

```python
# Additional imports for enhanced visualization and data export
import pandas as pd
import seaborn as sns
from sklearn.metrics import classification_report, confusion_matrix,␣
    ↪accuracy_score
from sklearn.metrics import precision_recall_fscore_support
```

```
import time
import datetime
import os

# Set style for better plots
plt.style.use('seaborn-v0_8')
sns.set_palette("husl")

# Create results directory
os.makedirs('results', exist_ok=True)
print("Results directory created: ./results/")
```

```
Results directory created: ./results/
```

[6]:
```
# Binary Activation Function
class BinaryActivation(torch.autograd.Function):
    """
    Binary activation function using the sign function.
    Forward: sign(x) = {-1 if x < 0, +1 if x >= 0}
    Backward: Straight-through estimator (STE) - passes gradients through␣
 ↪unchanged
    """

    @staticmethod
    def forward(ctx, input):
        # Apply sign function: -1 for negative, +1 for non-negative
        return torch.sign(input)

    @staticmethod
    def backward(ctx, grad_output):
        # Straight-through estimator: pass gradients through unchanged
        # This allows gradients to flow back during training
        return grad_output

def binary_activation(x):
    """Wrapper function for binary activation"""
    return BinaryActivation.apply(x)
```

[7]:
```
# Binary Linear Layer
class BinaryLinear(nn.Module):
    """
    Binary Linear layer with binary weights.
    Weights are binarized using the sign function during forward pass.
    """

    def __init__(self, in_features, out_features, bias=True):
        super(BinaryLinear, self).__init__()
```

```
        self.in_features = in_features
        self.out_features = out_features

        # Initialize weights using normal distribution
        self.weight = nn.Parameter(torch.randn(out_features, in_features) * 0.1)

        if bias:
            self.bias = nn.Parameter(torch.zeros(out_features))
        else:
            self.register_parameter('bias', None)

    def forward(self, input):
        # Binarize weights using sign function
        binary_weight = torch.sign(self.weight)

        # Perform linear transformation with binary weights
        output = F.linear(input, binary_weight, self.bias)

        return output

    def extra_repr(self):
        return f'in_features={self.in_features}, out_features={self.
 ↪out_features}, bias={self.bias is not None}'
```

[8]:

```
# Binary Neural Network Model
class BinaryNeuralNetwork(nn.Module):
    """
    Binary Neural Network for multiclass plant disease classification.

    Architecture:
    - Input: Flattened 224x224 RGB images (3*224*224 = 150528 features)
    - Hidden Layer: Binary linear layer with binary activation
    - Output Layer: Regular linear layer for class logits
    - Final: Softmax for multiclass prediction
    """

    def __init__(self, input_size=3*224*224, hidden_size=512, num_classes=3):
        super(BinaryNeuralNetwork, self).__init__()

        self.input_size = input_size
        self.hidden_size = hidden_size
        self.num_classes = num_classes

        # First layer: Regular linear layer (input preprocessing)
        self.input_layer = nn.Linear(input_size, hidden_size)

        # Hidden layer: Binary linear layer
```

```python
        self.hidden_layer = BinaryLinear(hidden_size, hidden_size)

        # Output layer: Regular linear layer for final classification
        self.output_layer = nn.Linear(hidden_size, num_classes)

        # Dropout for regularization
        self.dropout = nn.Dropout(0.2)

    def forward(self, x):
        # Flatten input if it's not already flattened
        if len(x.shape) > 2:
            x = x.view(x.size(0), -1)  # Flatten to (batch_size, input_size)

        # Input layer with ReLU activation
        x = F.relu(self.input_layer(x))
        x = self.dropout(x)

        # Hidden layer with binary weights and binary activation
        x = self.hidden_layer(x)
        x = binary_activation(x)  # Binary activation function
        x = self.dropout(x)

        # Output layer (no activation - raw logits)
        logits = self.output_layer(x)

        return logits

    def predict_proba(self, x):
        """Get class probabilities using softmax"""
        with torch.no_grad():
            logits = self.forward(x)
            probabilities = F.softmax(logits, dim=1)
        return probabilities

    def predict(self, x):
        """Get predicted class labels"""
        with torch.no_grad():
            logits = self.forward(x)
            predictions = torch.argmax(logits, dim=1)
        return predictions
```

[9]:
```python
# Enhanced Training and Evaluation Functions
def train_bnn(model, train_loader, criterion, optimizer, device, num_epochs=10):
    """
    Enhanced training function with detailed metrics collection
    """
    model.train()
```

```python
# Initialize tracking lists
train_losses = []
train_accuracies = []
epoch_times = []
learning_rates = []

# Detailed metrics per epoch
training_history = []

print(f"Starting training for {num_epochs} epochs...")
print("-" * 60)

start_time = time.time()

for epoch in range(num_epochs):
    epoch_start = time.time()

    running_loss = 0.0
    correct_predictions = 0
    total_samples = 0
    batch_losses = []

    # Training loop
    for batch_idx, (data, targets) in enumerate(train_loader):
        data, targets = data.to(device), targets.to(device)

        # Zero gradients
        optimizer.zero_grad()

        # Forward pass
        outputs = model(data)
        loss = criterion(outputs, targets)

        # Backward pass
        loss.backward()
        optimizer.step()

        # Statistics
        batch_loss = loss.item()
        running_loss += batch_loss
        batch_losses.append(batch_loss)

        _, predicted = torch.max(outputs.data, 1)
        total_samples += targets.size(0)
        correct_predictions += (predicted == targets).sum().item()
```

```
        # Calculate epoch metrics
        epoch_loss = running_loss / len(train_loader)
        epoch_accuracy = 100 * correct_predictions / total_samples
        epoch_time = time.time() - epoch_start
        current_lr = optimizer.param_groups[0]['lr']

        # Store metrics
        train_losses.append(epoch_loss)
        train_accuracies.append(epoch_accuracy)
        epoch_times.append(epoch_time)
        learning_rates.append(current_lr)

        # Store detailed history
        training_history.append({
            'epoch': epoch + 1,
            'loss': epoch_loss,
            'accuracy': epoch_accuracy,
            'time': epoch_time,
            'learning_rate': current_lr,
            'min_batch_loss': min(batch_losses),
            'max_batch_loss': max(batch_losses),
            'std_batch_loss': np.std(batch_losses)
        })

        # Progress display
        print(f'Epoch [{epoch+1:2d}/{num_epochs}] | Loss: {epoch_loss:.4f} | '
              f'Acc: {epoch_accuracy:6.2f}% | Time: {epoch_time:.2f}s | LR:␣
↪{current_lr:.6f}')

    total_time = time.time() - start_time
    print("-" * 60)
    print(f"Training completed in {total_time:.2f} seconds")
    print(f"Average epoch time: {np.mean(epoch_times):.2f}s")

    return train_losses, train_accuracies, training_history, epoch_times

def evaluate_bnn(model, test_loader, criterion, device, class_names):
    """
    Enhanced evaluation function with detailed metrics
    """
    model.eval()
    test_loss = 0.0
    correct_predictions = 0
    total_samples = 0

    all_predictions = []
    all_targets = []
```

```python
    all_probabilities = []

    with torch.no_grad():
        for data, targets in test_loader:
            data, targets = data.to(device), targets.to(device)

            outputs = model(data)
            loss = criterion(outputs, targets)

            test_loss += loss.item()
            probabilities = F.softmax(outputs, dim=1)
            _, predicted = torch.max(outputs.data, 1)

            total_samples += targets.size(0)
            correct_predictions += (predicted == targets).sum().item()

            # Store for detailed analysis
            all_predictions.extend(predicted.cpu().numpy())
            all_targets.extend(targets.cpu().numpy())
            all_probabilities.extend(probabilities.cpu().numpy())

    test_loss /= len(test_loader)
    test_accuracy = 100 * correct_predictions / total_samples

    print(f'Test Loss: {test_loss:.4f}, Test Accuracy: {test_accuracy:.2f}%')

    # Generate detailed classification report
    report = classification_report(all_targets, all_predictions,
                                 target_names=class_names, output_dict=True)

    # Calculate per-class metrics
    precision, recall, fscore, support = precision_recall_fscore_support(
        all_targets, all_predictions, average=None,␣
↪labels=range(len(class_names))
    )

    # Create detailed metrics dictionary
    detailed_metrics = {
        'test_loss': test_loss,
        'test_accuracy': test_accuracy,
        'predictions': all_predictions,
        'targets': all_targets,
        'probabilities': all_probabilities,
        'classification_report': report,
        'per_class_precision': precision,
        'per_class_recall': recall,
        'per_class_fscore': fscore,
```

```python
        'per_class_support': support
    }

    return detailed_metrics
```

[10]:

```python
# Load Real Plant Disease Dataset
from torchvision import datasets, transforms
from PIL import Image
import os

def load_plant_disease_dataset(dataset_path, image_size=224):
    """
    Load the real plant disease dataset from the specified path.
    Dataset structure:
    - dataset_path/Healthy_Soyabean/
    - dataset_path/rust/
    - dataset_path/Soyabean_Mosaic/
    """

    # Define transforms for preprocessing
    transform = transforms.Compose([
        transforms.Resize((image_size, image_size)),  # Resize to 224x224
        transforms.ToTensor(),  # Convert to tensor and normalize to [0,1]
        transforms.Normalize(mean=[0.485, 0.456, 0.406],
                           std=[0.229, 0.224, 0.225])  # ImageNet normalization
    ])

    # Load dataset using ImageFolder
    dataset = datasets.ImageFolder(root=dataset_path, transform=transform)

    # Convert to tensors
    data_loader = torch.utils.data.DataLoader(dataset, batch_size=len(dataset),␣
↪shuffle=False)
    X, y = next(iter(data_loader))

    # Print class mapping
    print("Class mapping:")
    for idx, class_name in enumerate(dataset.classes):
        print(f"  {idx}: {class_name}")

    return X, y, dataset.classes

# Load your real plant disease dataset
dataset_path = "/home/dragoon/Downloads/MH-SoyaHealthVision An Indian UAV and␣
↪Leaf Image Dataset for Integrated Crop Health Assessment/
↪Soyabean_UAV-Based_Image_Dataset"
```

```
# dataset_path = "/home/dragoon/Downloads/MH-SoyaHealthVision/
 ↪Soyabean_UAV-Based_Image_Dataset"
print("Loading real plant disease dataset...")
print(f"Dataset path: {dataset_path}")

X, y, class_names = load_plant_disease_dataset(dataset_path, image_size=224)

print(f"\nDataset loaded successfully!")
print(f"Dataset shape: {X.shape}")
print(f"Labels shape: {y.shape}")
print(f"Number of classes: {len(torch.unique(y))}")
print(f"Class distribution: {torch.bincount(y)}")
print(f"Class names: {class_names}")

# Display some dataset statistics
print(f"\nDataset Statistics:")
for i, class_name in enumerate(class_names):
    count = (y == i).sum().item()
    print(f"  {class_name}: {count} images")
```

```
Loading real plant disease dataset…
Dataset path: /home/dragoon/Downloads/MH-SoyaHealthVision An Indian UAV and Leaf
Image Dataset for Integrated Crop Health Assessment/Soyabean_UAV-
Based_Image_Dataset
Class mapping:
  0: Healthy_Soyabean
  1: Soyabean Semilooper_Pest_Attack
  2: Soyabean_Mosaic
  3: rust

Dataset loaded successfully!
Dataset shape: torch.Size([2842, 3, 224, 224])
Labels shape: torch.Size([2842])
Number of classes: 4
Class distribution: tensor([ 280,  790,  772, 1000])
Class names: ['Healthy_Soyabean', 'Soyabean Semilooper_Pest_Attack',
'Soyabean_Mosaic', 'rust']

Dataset Statistics:
  Healthy_Soyabean: 280 images
  Soyabean Semilooper_Pest_Attack: 790 images
  Soyabean_Mosaic: 772 images
  rust: 1000 images
```

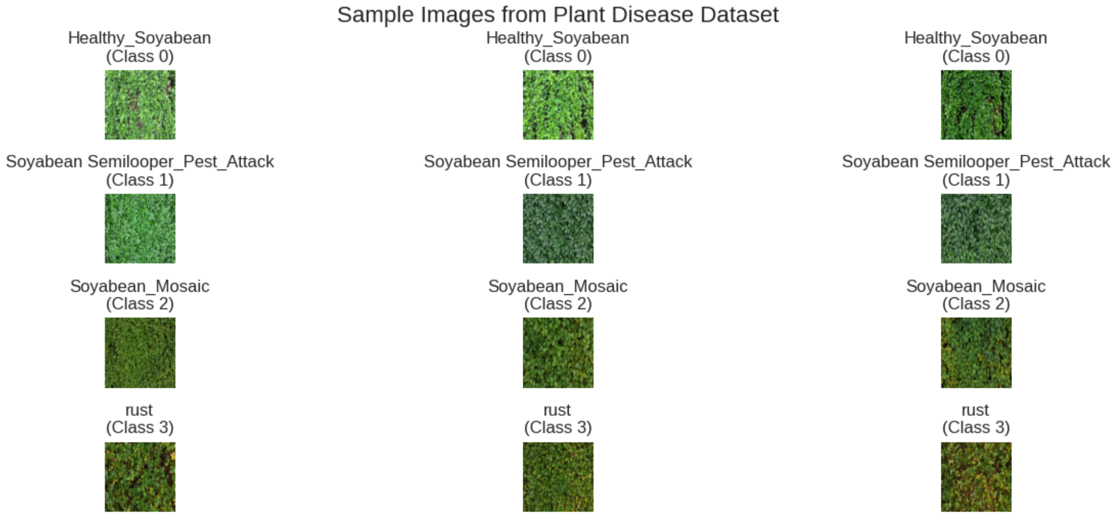
[11]:
```
# Split Dataset and Create Data Loaders
%pip install scikit-learn
from sklearn.model_selection import train_test_split
```

```
# Split dataset into train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

print(f"Training set: {X_train.shape[0]} samples")
print(f"Test set: {X_test.shape[0]} samples")

# Create data loaders
batch_size = 32

train_dataset = TensorDataset(X_train, y_train)
test_dataset = TensorDataset(X_test, y_test)

train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)

print(f"Number of training batches: {len(train_loader)}")
print(f"Number of test batches: {len(test_loader)}")
```

```
Requirement already satisfied: scikit-learn in ./.venv/lib/python3.11/site-
packages (1.7.0)
Requirement already satisfied: numpy>=1.22.0 in ./.venv/lib/python3.11/site-
packages (from scikit-learn) (2.3.1)
Requirement already satisfied: scipy>=1.8.0 in ./.venv/lib/python3.11/site-
packages (from scikit-learn) (1.16.0)
Requirement already satisfied: joblib>=1.2.0 in ./.venv/lib/python3.11/site-
packages (from scikit-learn) (1.5.1)
Requirement already satisfied: threadpoolctl>=3.1.0 in
./.venv/lib/python3.11/site-packages (from scikit-learn) (3.6.0)
Note: you may need to restart the kernel to use updated packages.
Training set: 2273 samples
Test set: 569 samples
Number of training batches: 72
Number of test batches: 18
```

[12]:
```
# Visualize Sample Images from the Dataset
def denormalize_image(tensor, mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.
↪225]):
    """Denormalize image tensor for visualization"""
    mean = torch.tensor(mean).view(3, 1, 1)
    std = torch.tensor(std).view(3, 1, 1)
    return tensor * std + mean

# Display sample images from each class
plt.figure(figsize=(15, 5))
```

```
samples_per_class = 3
for class_idx, class_name in enumerate(class_names):
    # Get indices for this class
    class_indices = torch.where(y == class_idx)[0]

    # Select random samples from this class
    random_indices = torch.randperm(len(class_indices))[:samples_per_class]
    sample_indices = class_indices[random_indices]

    for i, sample_idx in enumerate(sample_indices):
        plt.subplot(len(class_names), samples_per_class, class_idx *␣
 ↪samples_per_class + i + 1)

        # Get and denormalize image
        img = denormalize_image(X[sample_idx])
        img = torch.clamp(img, 0, 1)  # Ensure values are in [0,1]

        # Convert to numpy and transpose for matplotlib
        img_np = img.permute(1, 2, 0).numpy()

        plt.imshow(img_np)
        plt.title(f"{class_name}\n(Class {class_idx})")
        plt.axis('off')

plt.tight_layout()
plt.suptitle('Sample Images from Plant Disease Dataset', y=1.02, fontsize=16)
plt.show()

print(f"Sample images from your plant disease dataset:")
print(f"Classes: {', '.join(class_names)}")
print(f"Image size: 224x224 pixels")
print(f"Total images: {len(X)}")
```




```
Sample images from your plant disease dataset:
Classes: Healthy_Soyabean, Soyabean Semilooper_Pest_Attack, Soyabean_Mosaic,
rust
Image size: 224x224 pixels
Total images: 2842
```

[13]:
```
# Initialize and Train the BNN Model
# Model parameters
input_size = 3 * 224 * 224  # 224x224 RGB images (increased resolution)
hidden_size = 512
num_classes = len(class_names)  # Dynamic based on actual dataset

print(f"Model Configuration:")
print(f"  Input size: {input_size}")
print(f"  Hidden size: {hidden_size}")
print(f"  Number of classes: {num_classes}")
print(f"  Classes: {class_names}")

# Initialize model
model = BinaryNeuralNetwork(
    input_size=input_size,
    hidden_size=hidden_size,
    num_classes=num_classes
).to(device)

# Print model architecture
print("\nBinary Neural Network Architecture:")
print(model)
print(f"\nTotal parameters: {sum(p.numel() for p in model.parameters()):,}")
```

```
print(f"Trainable parameters: {sum(p.numel() for p in model.parameters() if p.
 ↪requires_grad):,}")

# Define loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001, weight_decay=1e-4)

# Train the model with enhanced tracking
print("\nStarting enhanced training with detailed metrics...")
train_losses, train_accuracies, training_history, epoch_times = train_bnn(
    model=model,
    train_loader=train_loader,
    criterion=criterion,
    optimizer=optimizer,
    device=device,
    num_epochs=20
)
```

```
Model Configuration:
  Input size: 150528
  Hidden size: 512
  Number of classes: 4
  Classes: ['Healthy_Soyabean', 'Soyabean Semilooper_Pest_Attack',
'Soyabean_Mosaic', 'rust']

Binary Neural Network Architecture:
BinaryNeuralNetwork(
  (input_layer): Linear(in_features=150528, out_features=512, bias=True)
  (hidden_layer): BinaryLinear(in_features=512, out_features=512, bias=True)
  (output_layer): Linear(in_features=512, out_features=4, bias=True)
  (dropout): Dropout(p=0.2, inplace=False)
)

Total parameters: 77,335,556
Trainable parameters: 77,335,556

Starting enhanced training with detailed metrics…
Starting training for 20 epochs…
------------------------------------------------------------
Epoch [ 1/20] | Loss: 1.0177 | Acc:  56.58% | Time: 3.72s | LR: 0.001000
Epoch [ 2/20] | Loss: 0.8065 | Acc:  64.32% | Time: 3.49s | LR: 0.001000
Epoch [ 3/20] | Loss: 0.7218 | Acc:  69.69% | Time: 3.49s | LR: 0.001000
Epoch [ 4/20] | Loss: 0.6995 | Acc:  68.50% | Time: 3.49s | LR: 0.001000
Epoch [ 5/20] | Loss: 0.6289 | Acc:  72.94% | Time: 3.48s | LR: 0.001000
Epoch [ 6/20] | Loss: 0.6023 | Acc:  74.88% | Time: 3.49s | LR: 0.001000
Epoch [ 7/20] | Loss: 0.6255 | Acc:  72.68% | Time: 3.49s | LR: 0.001000
Epoch [ 8/20] | Loss: 0.6125 | Acc:  74.44% | Time: 3.48s | LR: 0.001000
Epoch [ 9/20] | Loss: 0.6179 | Acc:  74.66% | Time: 3.47s | LR: 0.001000
```

```
Epoch [10/20] | Loss: 0.6904 | Acc:  71.01% | Time: 3.48s | LR: 0.001000
Epoch [11/20] | Loss: 0.6373 | Acc:  72.20% | Time: 3.47s | LR: 0.001000
Epoch [12/20] | Loss: 0.6937 | Acc:  71.54% | Time: 3.47s | LR: 0.001000
Epoch [13/20] | Loss: 0.7616 | Acc:  66.78% | Time: 3.46s | LR: 0.001000
Epoch [14/20] | Loss: 0.6925 | Acc:  70.66% | Time: 3.47s | LR: 0.001000
Epoch [15/20] | Loss: 0.7682 | Acc:  65.24% | Time: 3.47s | LR: 0.001000
Epoch [16/20] | Loss: 0.8242 | Acc:  63.97% | Time: 3.47s | LR: 0.001000
Epoch [17/20] | Loss: 0.9051 | Acc:  59.17% | Time: 3.48s | LR: 0.001000
Epoch [18/20] | Loss: 0.9313 | Acc:  59.04% | Time: 3.47s | LR: 0.001000
Epoch [19/20] | Loss: 1.0035 | Acc:  57.11% | Time: 3.47s | LR: 0.001000
Epoch [20/20] | Loss: 1.0514 | Acc:  54.73% | Time: 3.47s | LR: 0.001000
------------------------------------------------------------
Training completed in 69.82 seconds
Average epoch time: 3.49s
```

[14]:

```python
# Enhanced Model Evaluation and Comprehensive Visualization
print("\nEvaluating model with detailed metrics...")
detailed_metrics = evaluate_bnn(model, test_loader, criterion, device,␣
 ↪class_names)

# Create comprehensive visualizations
fig = plt.figure(figsize=(20, 15))

# 1. Training Loss and Accuracy
plt.subplot(3, 4, 1)
plt.plot(range(1, len(train_losses) + 1), train_losses, 'b-', linewidth=2,␣
 ↪label='Training Loss')
plt.title('Training Loss Over Epochs', fontsize=12, fontweight='bold')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.grid(True, alpha=0.3)
plt.legend()

plt.subplot(3, 4, 2)
plt.plot(range(1, len(train_accuracies) + 1), train_accuracies, 'r-',␣
 ↪linewidth=2, label='Training Accuracy')
plt.title('Training Accuracy Over Epochs', fontsize=12, fontweight='bold')
plt.xlabel('Epoch')
plt.ylabel('Accuracy (%)')
plt.grid(True, alpha=0.3)
plt.legend()

# 2. Training Time Analysis
plt.subplot(3, 4, 3)
plt.bar(range(1, len(epoch_times) + 1), epoch_times, alpha=0.7, color='green')
plt.title('Training Time per Epoch', fontsize=12, fontweight='bold')
plt.xlabel('Epoch')
```

```python
plt.ylabel('Time (seconds)')
plt.grid(True, alpha=0.3)

# 3. Confusion Matrix
plt.subplot(3, 4, 4)
cm = confusion_matrix(detailed_metrics['targets'],
 ↪detailed_metrics['predictions'])
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=class_names, yticklabels=class_names)
plt.title('Confusion Matrix', fontsize=12, fontweight='bold')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')

# 4. Per-Class Performance
plt.subplot(3, 4, 5)
metrics_df = pd.DataFrame({
    'Precision': detailed_metrics['per_class_precision'],
    'Recall': detailed_metrics['per_class_recall'],
    'F1-Score': detailed_metrics['per_class_fscore']
}, index=class_names)

metrics_df.plot(kind='bar', ax=plt.gca(), width=0.8)
plt.title('Per-Class Performance Metrics', fontsize=12, fontweight='bold')
plt.ylabel('Score')
plt.legend(loc='upper right')
plt.xticks(rotation=45)

# 5. Class Distribution
plt.subplot(3, 4, 6)
class_counts = [sum(1 for label in detailed_metrics['targets'] if label == i)
 ↪for i in range(len(class_names))]
plt.pie(class_counts, labels=class_names, autopct='%1.1f%%', startangle=90)
plt.title('Test Set Class Distribution', fontsize=12, fontweight='bold')

# 6. Loss Smoothness (Moving Average)
plt.subplot(3, 4, 7)
window_size = 5
if len(train_losses) >= window_size:
    smoothed_loss = pd.Series(train_losses).rolling(window=window_size).mean()
    plt.plot(range(1, len(train_losses) + 1), train_losses, 'b-', alpha=0.3,
 ↪label='Raw Loss')
    plt.plot(range(1, len(smoothed_loss) + 1), smoothed_loss, 'b-',
 ↪linewidth=2, label=f'{window_size}-Epoch Moving Avg')
    plt.legend()
else:
    plt.plot(range(1, len(train_losses) + 1), train_losses, 'b-', linewidth=2,
 ↪label='Training Loss')
```

```python
plt.title('Loss Smoothness Analysis', fontsize=12, fontweight='bold')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.grid(True, alpha=0.3)

# 7. Prediction Confidence Distribution
plt.subplot(3, 4, 8)
max_probs = [max(prob) for prob in detailed_metrics['probabilities']]
plt.hist(max_probs, bins=20, alpha=0.7, color='purple', edgecolor='black')
plt.title('Prediction Confidence Distribution', fontsize=12, fontweight='bold')
plt.xlabel('Maximum Probability')
plt.ylabel('Frequency')
plt.grid(True, alpha=0.3)

# 8. Learning Rate Over Time (if scheduler was used)
plt.subplot(3, 4, 9)
learning_rates = [history['learning_rate'] for history in training_history]
plt.plot(range(1, len(learning_rates) + 1), learning_rates, 'orange',␣
↪linewidth=2)
plt.title('Learning Rate Schedule', fontsize=12, fontweight='bold')
plt.xlabel('Epoch')
plt.ylabel('Learning Rate')
plt.grid(True, alpha=0.3)

# 9. Training Metrics Summary
plt.subplot(3, 4, 10)
summary_metrics = [
    detailed_metrics['test_accuracy'],
    np.mean(detailed_metrics['per_class_precision']) * 100,
    np.mean(detailed_metrics['per_class_recall']) * 100,
    np.mean(detailed_metrics['per_class_fscore']) * 100
]
metric_names = ['Accuracy', 'Avg Precision', 'Avg Recall', 'Avg F1-Score']
bars = plt.bar(metric_names, summary_metrics, color=['blue', 'green', 'orange',␣
↪'red'], alpha=0.7)
plt.title('Model Performance Summary', fontsize=12, fontweight='bold')
plt.ylabel('Score (%)')
plt.ylim(0, 100)
# Add value labels on bars
for bar, value in zip(bars, summary_metrics):
    plt.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 1,
             f'{value:.1f}%', ha='center', va='bottom', fontweight='bold')
plt.xticks(rotation=45)

# 10. Error Analysis
plt.subplot(3, 4, 11)
```

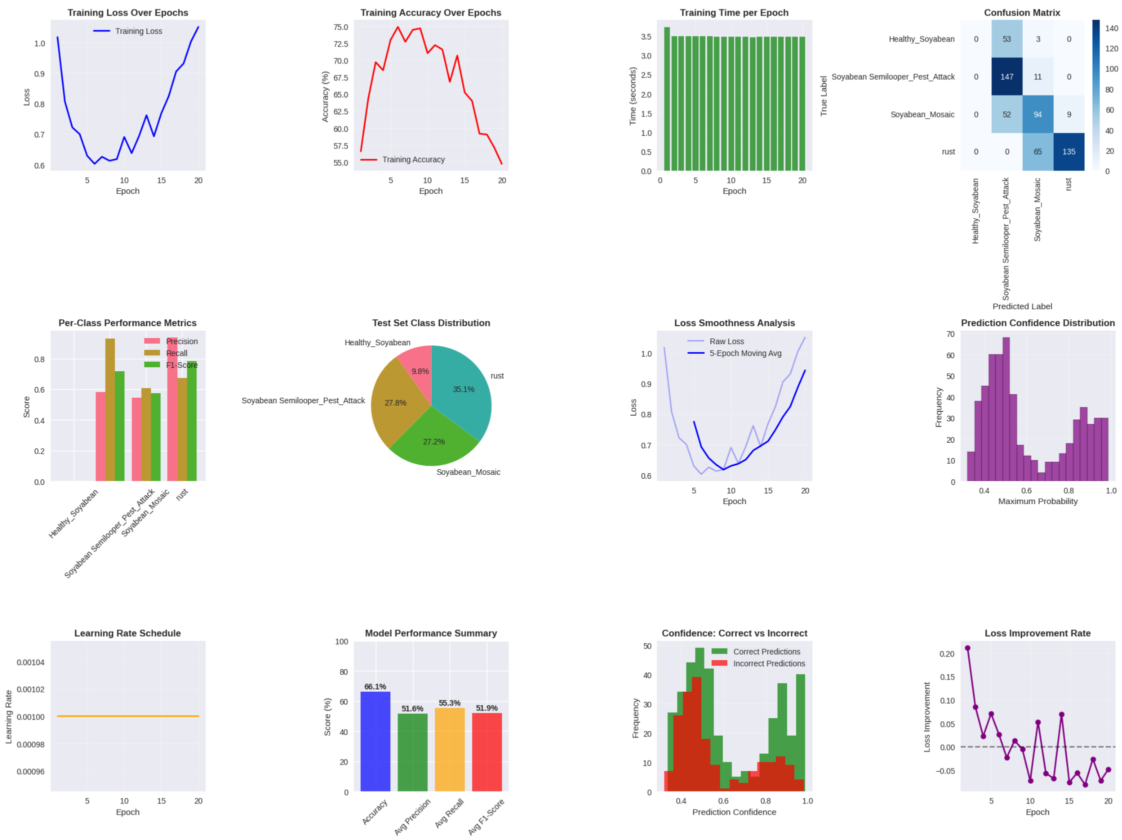
```
correct_mask = np.array(detailed_metrics['targets']) == np.
    array(detailed_metrics['predictions'])
correct_confidences = [max(prob) for i, prob in
    enumerate(detailed_metrics['probabilities']) if correct_mask[i]]
incorrect_confidences = [max(prob) for i, prob in
    enumerate(detailed_metrics['probabilities']) if not correct_mask[i]]

plt.hist(correct_confidences, bins=15, alpha=0.7, label='Correct Predictions',
    color='green')
plt.hist(incorrect_confidences, bins=15, alpha=0.7, label='Incorrect
    Predictions', color='red')
plt.title('Confidence: Correct vs Incorrect', fontsize=12, fontweight='bold')
plt.xlabel('Prediction Confidence')
plt.ylabel('Frequency')
plt.legend()
plt.grid(True, alpha=0.3)

# 11. Loss Improvement Rate
plt.subplot(3, 4, 12)
loss_improvements = [-1 * (train_losses[i] - train_losses[i-1]) for i in
    range(1, len(train_losses))]
plt.plot(range(2, len(train_losses) + 1), loss_improvements, 'purple',
    marker='o', linewidth=2)
plt.title('Loss Improvement Rate', fontsize=12, fontweight='bold')
plt.xlabel('Epoch')
plt.ylabel('Loss Improvement')
plt.grid(True, alpha=0.3)
plt.axhline(y=0, color='black', linestyle='--', alpha=0.5)

plt.tight_layout()
plt.savefig('results/comprehensive_training_analysis.png', dpi=300,
    bbox_inches='tight')
plt.show()

print(f"\n{'='*60}")
print("COMPREHENSIVE MODEL PERFORMANCE REPORT")
print(f"{'='*60}")
print(f"Overall Test Accuracy: {detailed_metrics['test_accuracy']:.2f}%")
print(f"Overall Test Loss: {detailed_metrics['test_loss']:.4f}")
print(f"Total Training Time: {sum(epoch_times):.2f} seconds")
print(f"Average Epoch Time: {np.mean(epoch_times):.2f} seconds")
print(f"\nPer-Class Performance:")
for i, class_name in enumerate(class_names):
    print(f"  {class_name}:")
    print(f"    Precision: {detailed_metrics['per_class_precision'][i]:.3f}")
    print(f"    Recall: {detailed_metrics['per_class_recall'][i]:.3f}")
```

```python
    print(f"    F1-Score: {detailed_metrics['per_class_fscore'][i]:.3f}")
    print(f"    Support: {detailed_metrics['per_class_support'][i]}")
print(f"{'='*60}")

# Test model predictions on a few samples
print("\nTesting model predictions:")
model.eval()
with torch.no_grad():
    # Get a small batch from test set
    test_samples = X_test[:5].to(device)
    test_labels = y_test[:5]

    # Get predictions
    logits = model(test_samples)
    probabilities = F.softmax(logits, dim=1)
    predicted_classes = torch.argmax(logits, dim=1)

    print("\nSample predictions:")
    for i in range(5):
        true_class_name = class_names[test_labels[i].item()]
        pred_class_name = class_names[predicted_classes[i].item()]

        print(f"Sample {i+1}:")
        print(f"  True label: {test_labels[i].item()} ({true_class_name})")
        print(f"  Predicted: {predicted_classes[i].item()} ({pred_class_name})")
        print(f"  Probabilities: {probabilities[i].cpu().numpy()}")

        # Show probability for each class
        for j, class_name in enumerate(class_names):
            prob = probabilities[i][j].item()
            print(f"    {class_name}: {prob:.3f}")
        print()
```

```
Evaluating model with detailed metrics…
Test Loss: 0.9215, Test Accuracy: 66.08%
```

```
/home/dragoon/coding/drone-crop/BNN/binary nerural
network/.venv/lib/python3.11/site-
packages/sklearn/metrics/_classification.py:1706: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
/home/dragoon/coding/drone-crop/BNN/binary nerural
network/.venv/lib/python3.11/site-
packages/sklearn/metrics/_classification.py:1706: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
```

```
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
/home/dragoon/coding/drone-crop/BNN/binary nerural
network/.venv/lib/python3.11/site-
packages/sklearn/metrics/_classification.py:1706: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
/home/dragoon/coding/drone-crop/BNN/binary nerural
network/.venv/lib/python3.11/site-
packages/sklearn/metrics/_classification.py:1706: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", result.shape[0])
```




```
============================================================
COMPREHENSIVE MODEL PERFORMANCE REPORT
============================================================
Overall Test Accuracy: 66.08%
Overall Test Loss: 0.9215
Total Training Time: 69.82 seconds
```

```
Average Epoch Time: 3.49 seconds

Per-Class Performance:
  Healthy_Soyabean:
    Precision: 0.000
    Recall: 0.000
    F1-Score: 0.000
    Support: 56
  Soyabean Semilooper_Pest_Attack:
    Precision: 0.583
    Recall: 0.930
    F1-Score: 0.717
    Support: 158
  Soyabean_Mosaic:
    Precision: 0.543
    Recall: 0.606
    F1-Score: 0.573
    Support: 155
  rust:
    Precision: 0.938
    Recall: 0.675
    F1-Score: 0.785
    Support: 200
============================================================

Testing model predictions:

Sample predictions:
Sample 1:
  True label: 1 (Soyabean Semilooper_Pest_Attack)
  Predicted: 1 (Soyabean Semilooper_Pest_Attack)
  Probabilities: [0.08531532 0.8166505  0.06423339 0.03380084]
    Healthy_Soyabean: 0.085
    Soyabean Semilooper_Pest_Attack: 0.817
    Soyabean_Mosaic: 0.064
    rust: 0.034

Sample 2:
  True label: 3 (rust)
  Predicted: 3 (rust)
  Probabilities: [0.07985441 0.12567203 0.26099566 0.53347784]
    Healthy_Soyabean: 0.080
    Soyabean Semilooper_Pest_Attack: 0.126
    Soyabean_Mosaic: 0.261
    rust: 0.533

Sample 3:
  True label: 1 (Soyabean Semilooper_Pest_Attack)
```

```
  Predicted: 1 (Soyabean Semilooper_Pest_Attack)
  Probabilities: [0.03808016 0.94920504 0.00672773 0.00598706]
    Healthy_Soyabean: 0.038
    Soyabean Semilooper_Pest_Attack: 0.949
    Soyabean_Mosaic: 0.007
    rust: 0.006

Sample 4:
  True label: 2 (Soyabean_Mosaic)
  Predicted: 1 (Soyabean Semilooper_Pest_Attack)
  Probabilities: [0.08994745 0.3865225  0.33603245 0.18749759]
    Healthy_Soyabean: 0.090
    Soyabean Semilooper_Pest_Attack: 0.387
    Soyabean_Mosaic: 0.336
    rust: 0.187

Sample 5:
  True label: 3 (rust)
  Predicted: 2 (Soyabean_Mosaic)
  Probabilities: [0.07532449 0.1616913  0.41420275 0.34878147]
    Healthy_Soyabean: 0.075
    Soyabean Semilooper_Pest_Attack: 0.162
    Soyabean_Mosaic: 0.414
    rust: 0.349
```

[15]:

```python
# Comprehensive CSV Data Export
print("\nExporting training data to CSV files...")

# 1. Training History CSV
training_df = pd.DataFrame(training_history)
training_df.to_csv('results/training_history.csv', index=False)
print("  Training history saved to: results/training_history.csv")

# 2. Detailed Test Results CSV
test_results = []
for i in range(len(detailed_metrics['targets'])):
    test_results.append({
        'sample_id': i,
        'true_label': detailed_metrics['targets'][i],
        'true_class': class_names[detailed_metrics['targets'][i]],
        'predicted_label': detailed_metrics['predictions'][i],
        'predicted_class': class_names[detailed_metrics['predictions'][i]],
        'correct': detailed_metrics['targets'][i] ==␣
 ↪detailed_metrics['predictions'][i],
        'confidence': max(detailed_metrics['probabilities'][i]),
```

```
        **{f'prob_{class_names[j]}': detailed_metrics['probabilities'][i][j] for j in range(len(class_names))}
    })

test_results_df = pd.DataFrame(test_results)
test_results_df.to_csv('results/test_predictions.csv', index=False)
print("  Test predictions saved to: results/test_predictions.csv")

# 3. Per-Class Performance Metrics CSV
per_class_metrics = pd.DataFrame({
    'class_name': class_names,
    'precision': detailed_metrics['per_class_precision'],
    'recall': detailed_metrics['per_class_recall'],
    'f1_score': detailed_metrics['per_class_fscore'],
    'support': detailed_metrics['per_class_support']
})
per_class_metrics.to_csv('results/per_class_metrics.csv', index=False)
print("  Per-class metrics saved to: results/per_class_metrics.csv")

# 4. Model Configuration and Final Results CSV
model_summary = {
    'parameter': [
        'model_type', 'input_size', 'hidden_size', 'num_classes',
        'num_epochs', 'batch_size', 'learning_rate', 'optimizer',
        'total_parameters', 'trainable_parameters',
        'final_train_loss', 'final_train_accuracy', 'test_loss', 'test_accuracy',
        'total_training_time', 'avg_epoch_time',
        'dataset_total_samples', 'train_samples', 'test_samples'
    ],
    'value': [
        'Binary Neural Network', input_size, hidden_size, num_classes,
        20, batch_size, 0.001, 'Adam',
        sum(p.numel() for p in model.parameters()),
        sum(p.numel() for p in model.parameters() if p.requires_grad),
        train_losses[-1], train_accuracies[-1],
        detailed_metrics['test_loss'], detailed_metrics['test_accuracy'],
        sum(epoch_times), np.mean(epoch_times),
        len(X), len(X_train), len(X_test)
    ]
}
model_summary_df = pd.DataFrame(model_summary)
model_summary_df.to_csv('results/model_summary.csv', index=False)
print("  Model summary saved to: results/model_summary.csv")

# 5. Confusion Matrix CSV
```

```
cm = confusion_matrix(detailed_metrics['targets'],␣
↪detailed_metrics['predictions'])
cm_df = pd.DataFrame(cm, index=[f'True_{name}' for name in class_names],
                     columns=[f'Pred_{name}' for name in class_names])
cm_df.to_csv('results/confusion_matrix.csv')
print("  Confusion matrix saved to: results/confusion_matrix.csv")

# 6. Training Progress Summary CSV
epoch_summary = []
for i in range(len(train_losses)):
    epoch_summary.append({
        'epoch': i + 1,
        'train_loss': train_losses[i],
        'train_accuracy': train_accuracies[i],
        'epoch_time': epoch_times[i],
        'cumulative_time': sum(epoch_times[:i+1]),
        'loss_improvement': 0 if i == 0 else train_losses[i-1] -␣
↪train_losses[i],
        'accuracy_improvement': 0 if i == 0 else train_accuracies[i] -␣
↪train_accuracies[i-1]
    })

epoch_summary_df = pd.DataFrame(epoch_summary)
epoch_summary_df.to_csv('results/epoch_summary.csv', index=False)
print("  Epoch summary saved to: results/epoch_summary.csv")

# 7. Binary Weights Analysis CSV
with torch.no_grad():
    hidden_weights = model.hidden_layer.weight.data.cpu().numpy()
    binary_weights = np.sign(hidden_weights)

    weights_analysis = {
        'layer': ['hidden_layer'],
        'total_weights': [hidden_weights.size],
        'positive_weights': [np.sum(binary_weights > 0)],
        'negative_weights': [np.sum(binary_weights < 0)],
        'zero_weights': [np.sum(binary_weights == 0)],
        'weight_mean': [np.mean(hidden_weights)],
        'weight_std': [np.std(hidden_weights)],
        'binary_weight_ratio': [np.sum(binary_weights > 0) / hidden_weights.
↪size]
    }

weights_analysis_df = pd.DataFrame(weights_analysis)
weights_analysis_df.to_csv('results/binary_weights_analysis.csv', index=False)
print("  Binary weights analysis saved to: results/binary_weights_analysis.csv")
```

```
# 8. Dataset Statistics CSV
dataset_stats = []
for i, class_name in enumerate(class_names):
    train_count = sum(1 for label in y_train if label == i)
    test_count = sum(1 for label in y_test if label == i)
    total_count = train_count + test_count

    dataset_stats.append({
        'class_name': class_name,
        'class_id': i,
        'train_samples': train_count,
        'test_samples': test_count,
        'total_samples': total_count,
        'train_percentage': (train_count / len(y_train)) * 100,
        'test_percentage': (test_count / len(y_test)) * 100,
        'overall_percentage': (total_count / len(y)) * 100
    })

dataset_stats_df = pd.DataFrame(dataset_stats)
dataset_stats_df.to_csv('results/dataset_statistics.csv', index=False)
print("  Dataset statistics saved to: results/dataset_statistics.csv")

# Create a comprehensive summary report
print(f"\n{'='*80}")
print("CSV FILES EXPORTED SUCCESSFULLY")
print(f"{'='*80}")
print("The following CSV files have been created in the 'results/' directory:")
print("1. training_history.csv - Detailed epoch-by-epoch training metrics")
print("2. test_predictions.csv - Individual test sample predictions and␣
↪probabilities")
print("3. per_class_metrics.csv - Precision, recall, F1-score for each class")
print("4. model_summary.csv - Model configuration and final performance")
print("5. confusion_matrix.csv - Confusion matrix data")
print("6. epoch_summary.csv - Training progress with improvements")
print("7. binary_weights_analysis.csv - Analysis of binary weight distribution")
print("8. dataset_statistics.csv - Dataset composition and class distribution")
print(f"{'='*80}")

# Display sample of key CSV files
print("\nSample of Training History:")
print(training_df.head())
print("\nSample of Test Predictions:")
print(test_results_df.head())
print("\nPer-Class Metrics:")
print(per_class_metrics)
```

```
Exporting training data to CSV files…
```

```
 Training history saved to: results/training_history.csv
 Test predictions saved to: results/test_predictions.csv
 Per-class metrics saved to: results/per_class_metrics.csv
 Model summary saved to: results/model_summary.csv
 Confusion matrix saved to: results/confusion_matrix.csv
 Epoch summary saved to: results/epoch_summary.csv
 Binary weights analysis saved to: results/binary_weights_analysis.csv
 Dataset statistics saved to: results/dataset_statistics.csv

================================================================================
CSV FILES EXPORTED SUCCESSFULLY
================================================================================
The following CSV files have been created in the 'results/' directory:
1. training_history.csv - Detailed epoch-by-epoch training metrics
2. test_predictions.csv - Individual test sample predictions and probabilities
3. per_class_metrics.csv - Precision, recall, F1-score for each class
4. model_summary.csv - Model configuration and final performance
5. confusion_matrix.csv - Confusion matrix data
6. epoch_summary.csv - Training progress with improvements
7. binary_weights_analysis.csv - Analysis of binary weight distribution
8. dataset_statistics.csv - Dataset composition and class distribution
================================================================================

Sample of Training History:
   epoch      loss   accuracy      time  learning_rate  min_batch_loss  \
0      1  1.017667  56.577211  3.723100          0.001        0.637834
1      2  0.806459  64.320282  3.494545          0.001        0.471640
2      3  0.721814  69.687637  3.491834          0.001        0.516664
3      4  0.699459  68.499780  3.492792          0.001        0.090115
4      5  0.628917  72.943247  3.484508          0.001        0.291184

   max_batch_loss  std_batch_loss
0        2.485080        0.289303
1        1.157512        0.131777
2        1.849854        0.172884
3        1.158462        0.140914
4        1.007220        0.114069

Sample of Test Predictions:
   sample_id  true_label                       true_class  predicted_label  \
0          0           1  Soyabean Semilooper_Pest_Attack                1
1          1           3                             rust                3
2          2           1  Soyabean Semilooper_Pest_Attack                1
3          3           2                  Soyabean_Mosaic                1
4          4           3                             rust                2

                 predicted_class  correct  confidence  \
0  Soyabean Semilooper_Pest_Attack     True    0.816651
```

```
1                             rust     True    0.533478
2  Soyabean Semilooper_Pest_Attack     True    0.949205
3  Soyabean Semilooper_Pest_Attack    False    0.386523
4                  Soyabean_Mosaic    False    0.414203

   prob_Healthy_Soyabean  prob_Soyabean Semilooper_Pest_Attack  \
0               0.085315                              0.816651
1               0.079854                              0.125672
2               0.038080                              0.949205
3               0.089947                              0.386523
4               0.075324                              0.161691

   prob_Soyabean_Mosaic  prob_rust
0              0.064233   0.033801
1              0.260996   0.533478
2              0.006728   0.005987
3              0.336032   0.187498
4              0.414203   0.348781

Per-Class Metrics:
                        class_name  precision    recall  f1_score  support
0                 Healthy_Soyabean   0.000000  0.000000  0.000000       56
1  Soyabean Semilooper_Pest_Attack   0.583333  0.930380  0.717073      158
2                  Soyabean_Mosaic   0.543353  0.606452  0.573171      155
3                             rust   0.937500  0.675000  0.784884      200
```

[16]:

```
# Model Saving and Additional Analysis
print("\nSaving model and creating additional analyses...")

# Save the trained model
timestamp = datetime.datetime.now().strftime("%Y%m%d_%H%M%S")
model_path = f'results/bnn_plant_disease_model_{timestamp}.pth'
torch.save(model.state_dict(), model_path)
print(f"  Model saved to: {model_path}")

# Save model architecture info
model_info = {
    'model_class': 'BinaryNeuralNetwork',
    'input_size': input_size,
    'hidden_size': hidden_size,
    'num_classes': num_classes,
    'class_names': class_names,
    'timestamp': timestamp,
    'final_accuracy': detailed_metrics['test_accuracy'],
    'final_loss': detailed_metrics['test_loss']
}
```

```python
import json
with open(f'results/model_info_{timestamp}.json', 'w') as f:
    json.dump(model_info, f, indent=2)
print(f"  Model info saved to: results/model_info_{timestamp}.json")

# Create ROC Curves for each class (one-vs-rest)
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize

# Binarize the output for ROC calculation
y_test_bin = label_binarize(detailed_metrics['targets'], classes=range(len(class_names)))
y_score = np.array(detailed_metrics['probabilities'])

plt.figure(figsize=(15, 5))

# Plot ROC curve for each class
for i in range(len(class_names)):
    plt.subplot(1, 3, i+1)
    fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_score[:, i])
    roc_auc = auc(fpr, tpr)

    plt.plot(fpr, tpr, linewidth=2, label=f'ROC curve (AUC = {roc_auc:.3f})')
    plt.plot([0, 1], [0, 1], 'k--', linewidth=1)
    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'ROC Curve - {class_names[i]}')
    plt.legend(loc="lower right")
    plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.savefig('results/roc_curves.png', dpi=300, bbox_inches='tight')
plt.show()

# Create improvement trends visualization
plt.figure(figsize=(16, 8))

# Loss improvement over time
plt.subplot(2, 2, 1)
loss_smooth = pd.Series(train_losses).rolling(window=3, center=True).mean()
plt.plot(range(1, len(train_losses) + 1), train_losses, 'b-', alpha=0.5, label='Raw Loss')
plt.plot(range(1, len(loss_smooth) + 1), loss_smooth, 'b-', linewidth=2, label='Smoothed Loss')
plt.title('Training Loss Improvement Trend')
```

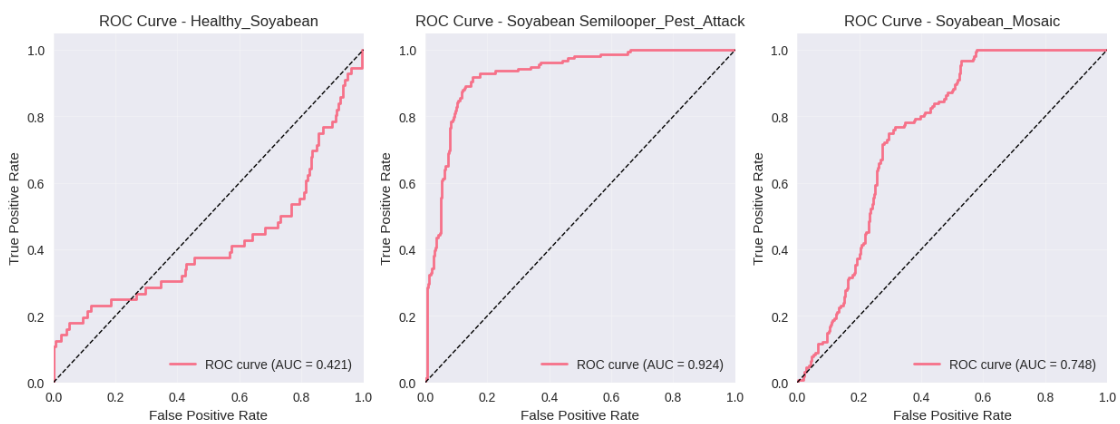
```
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.grid(True, alpha=0.3)

# Accuracy improvement over time
plt.subplot(2, 2, 2)
acc_smooth = pd.Series(train_accuracies).rolling(window=3, center=True).mean()
plt.plot(range(1, len(train_accuracies) + 1), train_accuracies, 'r-', alpha=0.
 ↪5, label='Raw Accuracy')
plt.plot(range(1, len(acc_smooth) + 1), acc_smooth, 'r-', linewidth=2,␣
 ↪label='Smoothed Accuracy')
plt.title('Training Accuracy Improvement Trend')
plt.xlabel('Epoch')
plt.ylabel('Accuracy (%)')
plt.legend()
plt.grid(True, alpha=0.3)

# Training efficiency (accuracy per time)
plt.subplot(2, 2, 3)
efficiency = np.array(train_accuracies) / np.array(epoch_times)
plt.plot(range(1, len(efficiency) + 1), efficiency, 'g-', linewidth=2,␣
 ↪marker='o')
plt.title('Training Efficiency (Accuracy/Time)')
plt.xlabel('Epoch')
plt.ylabel('Accuracy % per Second')
plt.grid(True, alpha=0.3)

# Convergence analysis
plt.subplot(2, 2, 4)
loss_changes = np.abs(np.diff(train_losses))
plt.semilogy(range(2, len(train_losses) + 1), loss_changes, 'purple',␣
 ↪linewidth=2, marker='s')
plt.title('Loss Change Magnitude (Convergence)')
plt.xlabel('Epoch')
plt.ylabel('|Loss Change| (log scale)')
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.savefig('results/improvement_trends.png', dpi=300, bbox_inches='tight')
plt.show()

# Final performance summary
print(f"\n{'='*80}")
print("FINAL BINARY NEURAL NETWORK PERFORMANCE SUMMARY")
print(f"{'='*80}")
print(f"Model: Binary Neural Network for Plant Disease Classification")
```

```python
print(f"Dataset: {len(class_names)} classes - {', '.join(class_names)}")
print(f"Total Images: {len(X)} (Train: {len(X_train)}, Test: {len(X_test)})")
print(f"Image Size: 224x224 RGB")
print(f"Model Parameters: {sum(p.numel() for p in model.parameters()):,}")
print(f"Training Epochs: 20")
print(f"Training Time: {sum(epoch_times):.2f} seconds")
print(f"")
print(f"FINAL RESULTS:")
print(f"  Test Accuracy: {detailed_metrics['test_accuracy']:.2f}%")
print(f"  Test Loss: {detailed_metrics['test_loss']:.4f}")
print(f"  Average Precision: {np.mean(detailed_metrics['per_class_precision']):.
  ↪3f}")
print(f"  Average Recall: {np.mean(detailed_metrics['per_class_recall']):.3f}")
print(f"  Average F1-Score: {np.mean(detailed_metrics['per_class_fscore']):.
  ↪3f}")
print(f"")
print(f"MODEL COMPRESSION:")
binary_params = sum(p.numel() for name, p in model.named_parameters() if␣
  ↪'hidden_layer.weight' in name)
total_params = sum(p.numel() for p in model.parameters())
print(f"  Binary Parameters: {binary_params:,} ({binary_params/total_params:.
  ↪1%} of total)")
print(f"  Theoretical Storage Reduction: ~{binary_params * 32 / total_params:.
  ↪1f}x for binary weights")
print(f"{'='*80}")
print("All results, graphs, and CSV files have been saved to the 'results/'␣
  ↪directory.")
print(f"{'='*80}")
```

```
Saving model and creating additional analyses…
  Model saved to: results/bnn_plant_disease_model_20250629_131745.pth
  Model info saved to: results/model_info_20250629_131745.json
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[16], line 39
     37 # Plot ROC curve for each class
     38 for i in range(len(class_names)):
---> 39     plt.subplot(1, 3, i+1)
     40     fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_score[:, i])
     41     roc_auc = auc(fpr, tpr)

File ~/coding/drone-crop/BNN/binary nerural network/.venv/lib/python3.11/
  ↪site-packages/matplotlib/pyplot.py:1552, in subplot(*args, **kwargs)
   1549 fig = gcf()
   1551 # First, search for an existing subplot with a matching spec.
```

```
-> 1552 key = SubplotSpec._from_subplot_args(fig, args)
   1554 for ax in fig.axes:
   1555     # If we found an Axes at the position, we can reuse it if the user␣
 ↪passed no
   1556     # kwargs or if the Axes class and kwargs are identical.
   1557     if (ax.get_subplotspec() == key
   1558         and (kwargs == {}
   1559              or (ax._projection_init
   1560                  == fig._process_projection_requirements(**kwargs)))):

File ~/coding/drone-crop/BNN/binary nerural network/.venv/lib/python3.11/
 ↪site-packages/matplotlib/gridspec.py:589, in SubplotSpec.
 ↪_from_subplot_args(figure, args)
    587 else:
    588     if not isinstance(num, Integral) or num < 1 or num > rows*cols:
--> 589         raise ValueError(
    590             f"num must be an integer with 1 <= num <= {rows*cols}, "
    591             f"not {num!r}"
    592         )
    593     i = j = num
    594 return gs[i-1:j]

ValueError: num must be an integer with 1 <= num <= 3, not 4
```



[ ]:
```python
# Model Analysis and Binary Weights Visualization
def analyze_binary_weights(model):
    """Analyze the binary weights in the model"""
    print("Binary Weights Analysis:")
    print("=" * 50)

    # Analyze hidden layer binary weights
    with torch.no_grad():
```

```python
        hidden_weights = model.hidden_layer.weight
        binary_weights = torch.sign(hidden_weights)

        print(f"Hidden layer weights shape: {hidden_weights.shape}")
        print(f"Original weights - Mean: {hidden_weights.mean():.4f}, Std:␣
↪{hidden_weights.std():.4f}")
        print(f"Binary weights - Unique values: {torch.unique(binary_weights)}")
        print(f"Binary weights - Distribution: +1: {(binary_weights == 1).sum().
↪item()}, -1: {(binary_weights == -1).sum().item()}")

        # Plot weight distributions
        plt.figure(figsize=(12, 4))

        plt.subplot(1, 2, 1)
        plt.hist(hidden_weights.cpu().numpy().flatten(), bins=50, alpha=0.7,␣
↪color='blue')
        plt.title('Original Weights Distribution')
        plt.xlabel('Weight Value')
        plt.ylabel('Frequency')
        plt.grid(True)

        plt.subplot(1, 2, 2)
        plt.hist(binary_weights.cpu().numpy().flatten(), bins=3, alpha=0.7,␣
↪color='red')
        plt.title('Binary Weights Distribution')
        plt.xlabel('Binary Weight Value')
        plt.ylabel('Frequency')
        plt.grid(True)

        plt.tight_layout()
        plt.show()

# Analyze the trained model
analyze_binary_weights(model)

# Calculate model size reduction
def calculate_model_compression():
    """Calculate the compression achieved by using binary weights"""

    # Count parameters in binary layers
    binary_params = sum(p.numel() for name, p in model.named_parameters()
                       if 'hidden_layer.weight' in name)

    # Total parameters
    total_params = sum(p.numel() for p in model.parameters())

    print(f"\nModel Compression Analysis:")
```

```python
    print(f"Total parameters: {total_params:,}")
    print(f"Binary parameters: {binary_params:,}")
    print(f"Binary ratio: {binary_params/total_params:.2%}")

    # In practice, binary weights can be stored using 1 bit vs 32 bits (float32)
    # This gives approximately 32x compression for binary weights
    theoretical_compression = binary_params * 32 / (total_params * 32 -
 ↪binary_params * 31)
    print(f"Theoretical storage compression: {theoretical_compression:.1f}x")

calculate_model_compression()
```

1.2 Using Real Plant Disease Data

To use this BNN with real plant disease images, follow these steps:

1.2.1 1. Data Preparation

```python
# Example for loading real plant disease dataset
from torchvision import datasets, transforms
from PIL import Image

# Define transforms for 224x224 RGB images
transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],
                         std=[0.229, 0.224, 0.225])
])

# Load your dataset (example structure)
# dataset/
#     healthy/
#     disease1/
#     disease2/

dataset = datasets.ImageFolder(root='path/to/your/dataset',
                               transform=transform)
```

1.2.2 2. Model Adaptation

- Adjust `num_classes` parameter based on your dataset
- Modify `hidden_size` for different model complexities
- Consider adding more binary layers for deeper networks

1.2.3 3. Training Tips

- Use data augmentation for better generalization
- Implement learning rate scheduling

- Add early stopping to prevent overfitting
- Consider using batch normalization before binary activations

1.2.4 4. Performance Optimization

- Experiment with different optimizers (SGD, AdamW)
- Try different initialization strategies for binary weights
- Implement gradient clipping for stable training
- Use mixed precision training for faster computation