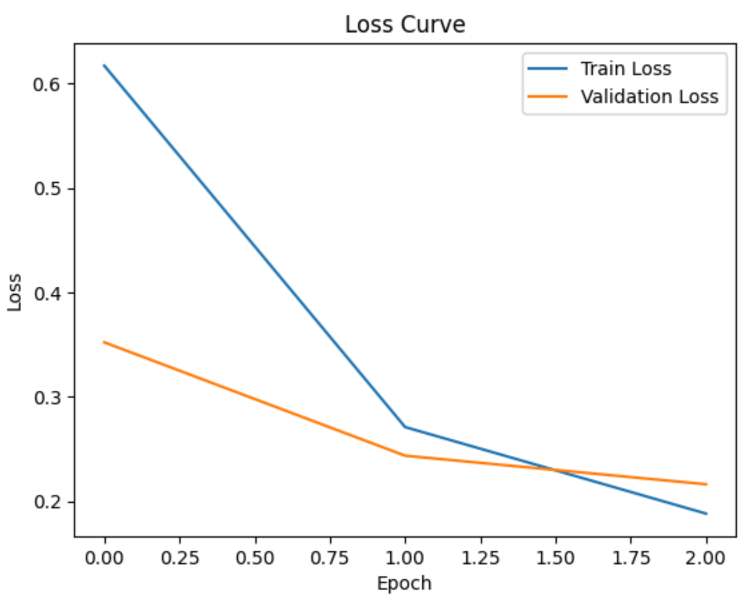
```
# Mount Google Drive and set paths
from google.colab import drive
drive.mount('/content/drive')

import os
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms, models
from torch.utils.data import DataLoader
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score, precision_score, recall_score, f1_score
from torchinfo import summary
from ptflops import get_model_complexity_info
import platform
import time
import matplotlib.pyplot as plt
from PIL import Image
import numpy as np
from itertools import product
import random

# Set dataset path
data_dir = '/content/drive/MyDrive/dataset'

# Transforms
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])
])

train_dir = os.path.join(data_dir, 'train')
valid_dir = os.path.join(data_dir, 'valid')
test_dir = os.path.join(data_dir, 'test')

train_data = datasets.ImageFolder(train_dir, transform=transform)
valid_data = datasets.ImageFolder(valid_dir, transform=transform)
test_data = datasets.ImageFolder(test_dir, transform=transform)

# Hyperparameter tuning configs
learning_rates = [0.001, 0.0005]
optimizers = ['adam', 'sgd']
batch_sizes = [32, 64]
epochs = 3

best_model = None
best_val_accuracy = 0
results = []
train_time = None
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

for lr, opt_type, batch_size in product(learning_rates, optimizers, batch_sizes):
    print(f"\nTraining with LR={lr}, Optimizer={opt_type}, Batch Size={batch_size}")

    train_loader = DataLoader(train_data, batch_size=batch_size, shuffle=True)
    valid_loader = DataLoader(valid_data, batch_size=batch_size)

    model = models.vgg19(pretrained=True)
    for param in model.features.parameters():
        param.requires_grad = False
    model.classifier[6] = nn.Linear(4096, 2)
    model = model.to(device)

    optimizer = optim.Adam(model.classifier.parameters(), lr=lr) if opt_type == 'adam' else optim.SGD(model.classifier.parameters(), lr=lr, m
    criterion = nn.CrossEntropyLoss()

    train_losses, val_losses = [], []
    train_accuracies = []
    start_time = time.time()

    best_val_loss = float('inf')
    early_stop_counter = 0
    patience = 2

    for epoch in range(epochs):
        model.train()
```

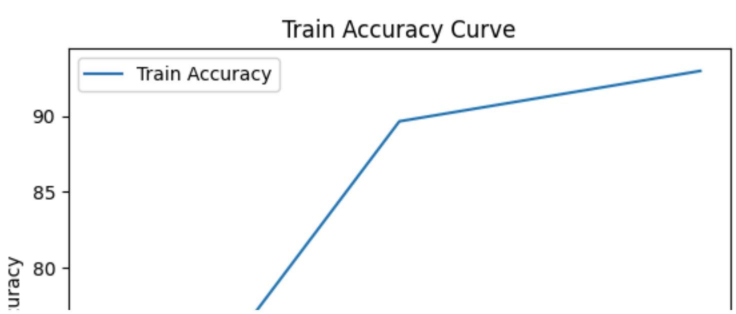
```
        train_loss, correct_train, total_train = 0, 0, 0
        for inputs, labels in train_loader:
            inputs, labels = inputs.to(device), labels.to(device)
            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            train_loss += loss.item()

            _, predicted = torch.max(outputs, 1)
            correct_train += (predicted == labels).sum().item()
            total_train += labels.size(0)

        avg_train_loss = train_loss / len(train_loader)
        train_losses.append(avg_train_loss)
        train_accuracy = 100 * correct_train / total_train
        train_accuracies.append(train_accuracy)

        model.eval()
        val_loss, correct, total = 0, 0, 0
        with torch.no_grad():
            for inputs, labels in valid_loader:
                inputs, labels = inputs.to(device), labels.to(device)
                outputs = model(inputs)
                loss = criterion(outputs, labels)
                val_loss += loss.item()
                _, predicted = torch.max(outputs, 1)
                correct += (predicted == labels).sum().item()
                total += labels.size(0)

        avg_val_loss = val_loss / len(valid_loader)
        val_losses.append(avg_val_loss)
        val_accuracy = 100 * correct / total

        print(f"Epoch {epoch+1}: Train Acc={train_accuracy:.2f}%, Train Loss={avg_train_loss:.4f}, Val Loss={avg_val_loss:.4f}, Val Acc={val_

        if avg_val_loss < best_val_loss:
            best_val_loss = avg_val_loss
            early_stop_counter = 0
        else:
            early_stop_counter += 1
            if early_stop_counter >= patience:
                print("Early stopping triggered.")
                break

    if val_accuracy > best_val_accuracy:
        best_val_accuracy = val_accuracy
        best_model = model

    train_time = time.time() - start_time
    results.append((lr, opt_type, batch_size, val_accuracy, train_accuracy))

# Plot Loss Curve
plt.plot(train_losses, label='Train Loss')
plt.plot(val_losses, label='Validation Loss')
plt.legend()
plt.title("Loss Curve")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.show()

# Plot Accuracy Curve
plt.plot(train_accuracies, label='Train Accuracy')
plt.title("Train Accuracy Curve")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.show()

print("\n=== Hyperparameter Tuning Summary ===")
for r in results:
    print(f"LR: {r[0]}, Optimizer: {r[1]}, Batch Size: {r[2]}, Val Accuracy: {r[3]:.2f}%, Train Accuracy: {r[4]:.2f}%")

# ---------- Final Evaluation on Test Set ---------- #
model = best_model
model.eval()
```

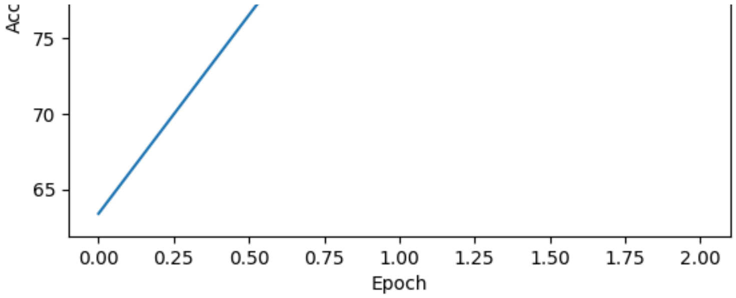
```
    correct, total = 0, 0
    all_preds, all_labels, all_probs = [], [], []
    start_test_time = time.time()

    with torch.no_grad():
        for inputs, labels in DataLoader(test_data, batch_size=32):
            inputs, labels = inputs.to(device), labels.to(device)
            outputs = model(inputs)
            probs = torch.nn.functional.softmax(outputs, dim=1)
            _, predicted = probs.max(1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()
            all_preds.extend(predicted.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())
            all_probs.extend(probs[:, 1].cpu().numpy())

    print(f"\nTest Accuracy: {100 * correct / total:.2f}%")

    # ---------- Metrics ---------- #
    precision = precision_score(all_labels, all_preds, average='macro')
    recall = recall_score(all_labels, all_preds, average='macro')
    f1 = f1_score(all_labels, all_preds, average='macro')
    roc_auc = roc_auc_score(all_labels, all_probs)

    print("\n📊 Final Test Performance:")
    print(f"✔ Precision: {precision:.2f}")
    print(f"✔ Recall: {recall:.2f}")
    print(f"✔ F1 Score: {f1:.2f}")
    print(f"✔ ROC-AUC: {roc_auc:.2f}")

    print("\nClassification Report:\n", classification_report(all_labels, all_preds, target_names=train_data.classes))
    print("Confusion Matrix:\n", confusion_matrix(all_labels, all_preds))

    # ---------- Computational Parameters ---------- #
    print("\n--- Model Info ---")
    total_params = sum(p.numel() for p in model.parameters())
    trainable_params = sum(p.numel() for p in model.parameters() if p.requires_grad)
    print(f"Total Parameters: {total_params}")
    print(f"Trainable Parameters: {trainable_params}")

    summary(model, input_size=(1, 3, 224, 224))
    with torch.cuda.device(0):
        macs, params = get_model_complexity_info(model, (3, 224, 224), as_strings=True, print_per_layer_stat=False)
        print(f"FLOPs: {macs}, Params: {params}")

    print("Training Platform:", platform.platform())
    print("CUDA Device:", torch.cuda.get_device_name(0) if torch.cuda.is_available() else "CPU")
    print(f"Total Training Time: {train_time:.2f} seconds")
    print(f"Inference Time on 1 image: {time.time() - start_test_time:.4f} seconds")

    # ---------- Robustness Test (Noise and Lighting) ---------- #
    transform_robust = transforms.Compose([
        transforms.Resize((224, 224)),
        transforms.ColorJitter(brightness=0.5),
        transforms.ToTensor(),
        transforms.Lambda(lambda x: x + 0.05 * torch.randn_like(x)),
        transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
    ])
    robust_data = datasets.ImageFolder(test_dir, transform=transform_robust)
    robust_loader = DataLoader(robust_data, batch_size=32)

    correct, total = 0, 0
    with torch.no_grad():
        for inputs, labels in robust_loader:
            inputs, labels = inputs.to(device), labels.to(device)
            outputs = model(inputs)
            _, predicted = torch.max(outputs, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()
    print(f"Robustness (Noise & Lighting) Accuracy: {100 * correct / total:.2f}%")

    # ---------- Visualization of Correct Predictions ---------- #
    correct_preds = [(img[0], p, l) for img, p, l in zip(test_data.imgs, all_preds, all_labels) if p == l]

    for i in range(min(5, len(correct_preds))):
        path, pred, label = correct_preds[i]
        img = Image.open(path)
        plt.imshow(img)
```

```
        plt.title(f"Correct ✅\nTrue & Predicted: {train_data.classes[pred]}")
        plt.axis('off')
        plt.show()

    # ---------- Save Model ---------- #
    torch.save(model.state_dict(), '/content/drive/MyDrive/vgg19_best_model.pth')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

Training with LR=0.001, Optimizer=adam, Batch Size=32
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for
  warnings.warn(msg)
Epoch 1: Train Acc=84.12%, Train Loss=1.4897, Val Loss=0.5440, Val Acc=93.41%
Epoch 2: Train Acc=95.30%, Train Loss=0.2759, Val Loss=0.6957, Val Acc=91.21%
Epoch 3: Train Acc=98.76%, Train Loss=0.1015, Val Loss=0.5356, Val Acc=92.31%

Training with LR=0.001, Optimizer=adam, Batch Size=64
Epoch 1: Train Acc=81.63%, Train Loss=1.0770, Val Loss=0.4079, Val Acc=86.81%
Epoch 2: Train Acc=96.13%, Train Loss=0.1870, Val Loss=0.1612, Val Acc=94.51%
Epoch 3: Train Acc=98.07%, Train Loss=0.0630, Val Loss=0.1220, Val Acc=94.51%

Training with LR=0.001, Optimizer=sgd, Batch Size=32
Epoch 1: Train Acc=84.39%, Train Loss=0.3560, Val Loss=0.1845, Val Acc=92.31%
Epoch 2: Train Acc=95.58%, Train Loss=0.1231, Val Loss=0.1338, Val Acc=94.51%
Epoch 3: Train Acc=97.24%, Train Loss=0.0799, Val Loss=0.1151, Val Acc=94.51%

Training with LR=0.001, Optimizer=sgd, Batch Size=64
Epoch 1: Train Acc=74.17%, Train Loss=0.4973, Val Loss=0.2846, Val Acc=90.11%
Epoch 2: Train Acc=92.68%, Train Loss=0.1850, Val Loss=0.1848, Val Acc=93.41%
Epoch 3: Train Acc=95.58%, Train Loss=0.1303, Val Loss=0.1488, Val Acc=93.41%

Training with LR=0.0005, Optimizer=adam, Batch Size=32
Epoch 1: Train Acc=88.40%, Train Loss=0.6003, Val Loss=0.2983, Val Acc=91.21%
Epoch 2: Train Acc=96.27%, Train Loss=0.1388, Val Loss=0.3776, Val Acc=86.81%
Epoch 3: Train Acc=97.65%, Train Loss=0.0905, Val Loss=0.2374, Val Acc=92.31%

Training with LR=0.0005, Optimizer=adam, Batch Size=64
Epoch 1: Train Acc=87.71%, Train Loss=0.3460, Val Loss=0.2662, Val Acc=92.31%
Epoch 2: Train Acc=96.96%, Train Loss=0.0745, Val Loss=0.1061, Val Acc=95.60%
Epoch 3: Train Acc=99.03%, Train Loss=0.0302, Val Loss=0.1968, Val Acc=96.70%

Training with LR=0.0005, Optimizer=sgd, Batch Size=32
Epoch 1: Train Acc=77.35%, Train Loss=0.4448, Val Loss=0.2410, Val Acc=87.91%
Epoch 2: Train Acc=94.06%, Train Loss=0.1690, Val Loss=0.1789, Val Acc=90.11%
Epoch 3: Train Acc=95.17%, Train Loss=0.1294, Val Loss=0.1537, Val Acc=93.41%

Training with LR=0.0005, Optimizer=sgd, Batch Size=64
Epoch 1: Train Acc=63.40%, Train Loss=0.6173, Val Loss=0.3521, Val Acc=90.11%
Epoch 2: Train Acc=89.64%, Train Loss=0.2709, Val Loss=0.2435, Val Acc=89.01%
Epoch 3: Train Acc=92.96%, Train Loss=0.1880, Val Loss=0.2161, Val Acc=90.11%
```








```
=== Hyperparameter Tuning Summary ===
LR: 0.001, Optimizer: adam, Batch Size: 32, Val Accuracy: 92.31%, Train Accuracy: 98.76%
LR: 0.001, Optimizer: adam, Batch Size: 64, Val Accuracy: 94.51%, Train Accuracy: 98.07%
LR: 0.001, Optimizer: sgd, Batch Size: 32, Val Accuracy: 94.51%, Train Accuracy: 97.24%
LR: 0.001, Optimizer: sgd, Batch Size: 64, Val Accuracy: 93.41%, Train Accuracy: 95.58%
LR: 0.0005, Optimizer: adam, Batch Size: 32, Val Accuracy: 92.31%, Train Accuracy: 97.65%
LR: 0.0005, Optimizer: adam, Batch Size: 64, Val Accuracy: 96.70%, Train Accuracy: 99.03%
LR: 0.0005, Optimizer: sgd, Batch Size: 32, Val Accuracy: 93.41%, Train Accuracy: 95.17%
LR: 0.0005, Optimizer: sgd, Batch Size: 64, Val Accuracy: 90.11%, Train Accuracy: 92.96%

Test Accuracy: 95.56%

📊 Final Test Performance:
✓ Precision: 0.96
✓ Recall: 0.96
✓ F1 Score: 0.96
✓ ROC-AUC: 1.00

Classification Report:
                 precision    recall  f1-score   support

    Degradable       0.94      0.98      0.96        45
Non degradable       0.98      0.93      0.95        45

      accuracy                           0.96        90
     macro avg       0.96      0.96      0.96        90
  weighted avg       0.96      0.96      0.96        90

Confusion Matrix:
 [[44  1]
 [ 3 42]]

--- Model Info ---
Total Parameters: 139578434
Trainable Parameters: 119554050
FLOPs: 19.68 GMac, Params: 119.55 M
Training Platform: Linux-6.1.123+-x86_64-with-glibc2.35
CUDA Device: Tesla T4
Total Training Time: 36.23 seconds
Inference Time on 1 image: 60.6988 seconds
Robustness (Noise & Lighting) Accuracy: 93.33%
/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 9989 (\N{WHITE HEAVY CHECK MARK}) missing frc
  fig.canvas.print_figure(bytes_io, **kw)
```

Correct □
True & Predicted: Degradable

Correct □
True & Predicted: Degradable

Correct ▯
True & Predicted: Degradable

Correct ▯
True & Predicted: Degradable

Correct ▯
True & Predicted: Degradable

```
!pip install torchinfo
```

```
Collecting torchinfo
  Downloading torchinfo-1.8.0-py3-none-any.whl.metadata (21 kB)
Downloading torchinfo-1.8.0-py3-none-any.whl (23 kB)
Installing collected packages: torchinfo
Successfully installed torchinfo-1.8.0
```

```
!pip install ptflops
```

```
Collecting ptflops
  Downloading ptflops-0.7.4-py3-none-any.whl.metadata (9.4 kB)
Requirement already satisfied: torch>=2.0 in /usr/local/lib/python3.11/dist-packages (from ptflops) (2.6.0+cu124)
Requirement already satisfied: filelock in /usr/local/lib/python3.11/dist-packages (from torch>=2.0->ptflops) (3.18.0)
Requirement already satisfied: typing-extensions>=4.10.0 in /usr/local/lib/python3.11/dist-packages (from torch>=2.0->ptflops) (4.14.1
Requirement already satisfied: networkx in /usr/local/lib/python3.11/dist-packages (from torch>=2.0->ptflops) (3.5)
```