Documentation of the Three Architectures

1) ResNet Implementation from scratch:

What is ResNet?

ResNet (Residual Network) was introduced in the paper *"Deep Residual Learning for Image Recognition"* by Kaiming He et al., 2015 (Link).

- **Key Idea:** Uses residual connections (shortcuts) to allow information to skip layers, mitigating the vanishing gradient problem in deep networks.
- **Why Residuals Work:** Instead of learning a full mapping, residual blocks let the model learn the difference (residual) between input and output, simplifying optimization.

Key Features of ResNet:

- **Residual Connections:** ResNet introduces shortcut connections to bypass one or more layers, solving the vanishing gradient problem.
- **Bottleneck Blocks:** Efficiently reduce computation using 1x1 convolutions.
- **Scalability:** Enables the training of networks with hundreds or thousands of layers (e.g., ResNet-50, ResNet-101).

Advantages of ResNet:

1. **Deeper Networks:** Residual connections enable the effective training of deep networks without performance degradation.
2. **Gradient Flow:** Shortcut connections help gradients flow backward without vanishing.
3. **Feature Reuse:** Reuses features from earlier layers, improving efficiency and accuracy.

Step-by-Step Code Explanation:

1)Dataset Preparation

```
import os
import pandas as pd
import numpy as np
import torch
import torch.nn as nn
from sklearn.preprocessing import label_binarize
import torchvision.transforms as transforms
from torchvision import datasets, transforms
from torch.utils.data import DataLoader, Dataset
from torch.utils.data.sampler import SubsetRandomSampler
import torch.optim as optim
from sklearn.metrics import accuracy_score, f1_score, confusion_matrix, roc_curve, auc
from torch.optim.lr_scheduler import StepLR
from tqdm import tqdm
import seaborn as sns
import matplotlib.pyplot as plt
```

- **Purpose**: **Import necessary libraries.**
  - `torch`: **PyTorch for defining and training the model.**
  - `torchvision`: **Utilities for image datasets and transformations.**
  - `sklearn`: **Used for evaluation metrics (e.g., accuracy, F1-score).**
  - `matplotlib/seaborn`: **For visualizations (confusion matrices, ROC).**

2)Preprocessing and Data Augmentation

Step 1: Compute Dataset Statistics

```
# Step 1: Define the transform for calculating mean and std
first_transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
])

# Step 2: Load the training dataset for normalization
train_dataset = datasets.ImageFolder(root=train_dir, transform=first_transform)

# Step 3: Calculate mean and std
def calculate_mean_std(dataloader):
    mean = 0.0
    std = 0.0
    total_imgs = 0
    for images, _ in dataloader:
        batch_mean = torch.mean(images, dim=[0, 2, 3])
        batch_std = torch.std(images, dim=[0, 2, 3])
        batch_size = images.size(0)
        mean += batch_mean * batch_size
        std += batch_std * batch_size
        total_imgs += batch_size
    mean /= total_imgs
    std /= total_imgs
    return mean, std
dataloader = DataLoader(train_dataset, batch_size=64, shuffle=False)
mean, std = calculate_mean_std(dataloader)
print(f"Dataset Mean: {mean}, Dataset Std: {std}")
```

Explanation:

1. **Initial Transformation:**
   - **Resizes all images to 224x224.**
   - **Converts images into tensors.**
2. **Calculate Mean/Std: Used for normalizing pixel values during training.**
   - **Mean: Average pixel value across dataset.**
   - **Std: Measures pixel value variation.**

3. Why 224x224? This size is widely used in pretrained models (e.g., ImageNet) and balances computational efficiency with feature extraction. Smaller images might lose detail, while larger images require more computation.

Step 2: Final Transformations

```
train_transform = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
    transforms.Normalize(mean=mean, std=std),
])

val_transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize(mean=mean, std=std),
])
```

- **Augmentation (Training Only):**
  - `RandomResizedCrop`: Randomly crops images for added diversity.
  - `RandomHorizontalFlip`: Flips images horizontally to improve robustness.
- **Normalization:**
  - Centers pixel values around 0 for faster convergence.

Step 3: Data Loading

```
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=batch_size, shuffle=False)
test_dataset = DataLoader(test_dataset,batch_size = batch_size , shuffle=False)
```

DataLoader: Efficiently batches data for training and evaluation.

- `shuffle=True` **ensures randomness for training.**

ResNet Architecture

3)Bottleneck Block

Why Use Bottleneck Blocks?

- **Efficiency: A bottleneck block reduces computation by compressing the number of channels using 1x1 convolutions.**
- **Structure:**
  - **First, reduce dimensions using 1x1 convolutions.**
  - **Then apply 3x3 convolutions for feature extraction.**
  - **Finally, expand dimensions back using another 1x1 convolution.**

In [5]:

```
class BottleneckBlock(nn.Module):
    def __init__(self, in_channels, out_channels, stride=1, downsample=None):
        super(BottleneckBlock, self).__init__()
        self.conv1 = nn.Sequential(
            nn.Conv2d(in_channels, out_channels, kernel_size=1, stride=1, bias=False),
            nn.BatchNorm2d(out_channels),
            nn.ReLU()
        )
        self.conv2 = nn.Sequential(
            nn.Conv2d(out_channels, out_channels, kernel_size=3, stride=stride, padding=1, bias=False),
            nn.BatchNorm2d(out_channels),
            nn.ReLU()
        )
        self.conv3 = nn.Sequential(
            nn.Conv2d(out_channels, out_channels * 4, kernel_size=1, stride=1, bias=False),
            nn.BatchNorm2d(out_channels * 4)
        )
        self.downsample = downsample
        self.relu = nn.ReLU()
```

Explanation:

1. **Conv1 (1x1 Convolution):**
   - **Reduces the number of channels, making subsequent computations more efficient.**
2. **Conv2 (3x3 Convolution):**

    - Extracts spatial features. The stride may be 2 for downsampling.
    - Padding ensures that spatial dimensions remain consistent.
3. Conv3 (1x1 Convolution):
    - Expands the number of channels to match the input for residual addition.
4. Downsample:
    - Ensures that the dimensions of the input match the output if they differ (e.g., due to stride).

4)Residual Connection

```
    def forward(self, x):
        residual = x
        out = self.conv1(x)
        out = self.conv2(out)
        out = self.conv3(out)
        if self.downsample:
            residual = self.downsample(x)
        out += residual
        out = self.relu(out)
        return out
```

Key Insight:

- Residual connections allow gradients to flow directly through the identity path, mitigating the vanishing gradient problem.
- The network learns residual mappings (differences) instead of full transformations, simplifying optimization.

5)ResNet Class

In [6]:
```
class ResNet(nn.Module):
    def __init__(self, block, layers, num_classes=5749):
        super(ResNet, self).__init__()
        self.inplanes = 64
        self.conv1 = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=7, stride=2, padding=3, bias=False),
            nn.BatchNorm2d(64),
            nn.ReLU()
        )
        self.maxpool = nn.MaxPool2d(kernel_size=3, stride=2, padding=1)
        self.layer0 = self._make_layer(block, 64, layers[0], stride=1)
        self.layer1 = self._make_layer(block, 128, layers[1], stride=2)
        self.layer2 = self._make_layer(block, 256, layers[2], stride=2)
        self.layer3 = self._make_layer(block, 512, layers[3], stride=2)
        self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
        self.fc = nn.Linear(512 * 4, num_classes)
```

Explanation:

1. **Conv1**:
   - **Applies a large kernel (7x7) convolution to extract initial features.**
   - **Stride (step) of 2 reduces spatial dimensions by half.**
2. **MaxPool:**
   - **Further reduces spatial dimensions, retaining key features.**
3. **Residual Layers:**
   - **`_make_layer` stacks multiple bottleneck blocks, each focusing on feature extraction at different scales.**
4. **Global Pooling:**
   - **`AdaptiveAvgPool2d((1,1))` converts feature maps to a fixed size, regardless of input dimensions.**
5. **Fully Connected Layer:**
   - **Maps the extracted features to class probabilities.**

6) Training Loop

```python
# Configuration
batch_size = 64
epochs = 20
lr = 0.001
weight_decay = 1e-4
step_size = 10
gamma = 0.1


# Model setup
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = model.to(device)
```

```python
# Loss, optimizer, scheduler
criterion = nn.CrossEntropyLoss()
optimizer = optim.AdamW(model.parameters(), lr=lr, weight_decay=weight_decay)
scheduler = StepLR(optimizer, step_size=step_size, gamma=gamma)

# Training and Validation
for epoch in range(epochs):
    # Training Phase
    model.train()
    train_loss = 0.0
    train_preds, train_labels = [], []

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

        # Forward pass
        outputs = model(images)
        loss = criterion(outputs, labels)

        # Backpropagation
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        # Record loss and predictions
        train_loss += loss.item()
        _, preds = torch.max(outputs, 1)
        train_preds.extend(preds.cpu().numpy())
        train_labels.extend(labels.cpu().numpy())
```

```python
    # Scheduler step
    scheduler.step()

    train_accuracy = accuracy_score(train_labels, train_preds)

    # Validation Phase
    model.eval()
    val_loss = 0.0
    val_preds, val_labels = [], []

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

            outputs = model(images)
            loss = criterion(outputs, labels)

            val_loss += loss.item()
            _, preds = torch.max(outputs, 1)
            val_preds.extend(preds.cpu().numpy())
            val_labels.extend(labels.cpu().numpy())

    val_accuracy = accuracy_score(val_labels, val_preds)

    print(f"Epoch [{epoch+1}/{epochs}], "
          f"Train Loss: {train_loss/len(train_loader):.4f}, Train Accuracy: {train_accuracy*100:.2f}%, "
          f"Val Loss: {val_loss/len(val_loader):.4f}, Val Accuracy: {val_accuracy*100:.2f}%")
```

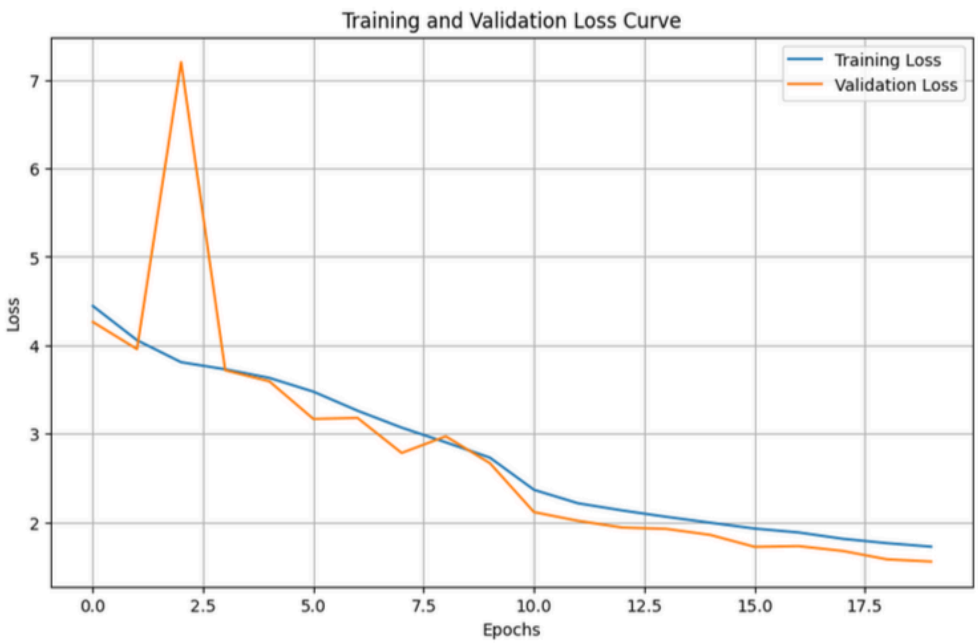
Explanation:

1. Loss Calculation:
    - `CrossEntropyLoss` computes the difference between predicted and true labels.
2. Backpropagation:
    - `optimizer.zero_grad()` clears gradients to avoid accumulation.
    - `loss.backward()` computes gradients.
    - `optimizer.step()` updates weights.
3. Learning Rate Scheduler:
    - Reduces the learning rate after every 10 epochs to improve convergence (`gamma=0.1`)..
4. Evaluation**:**
    - `model.eval()` disables dropout and batch normalization.
    - Validation metrics ensure the model generalizes to unseen data.

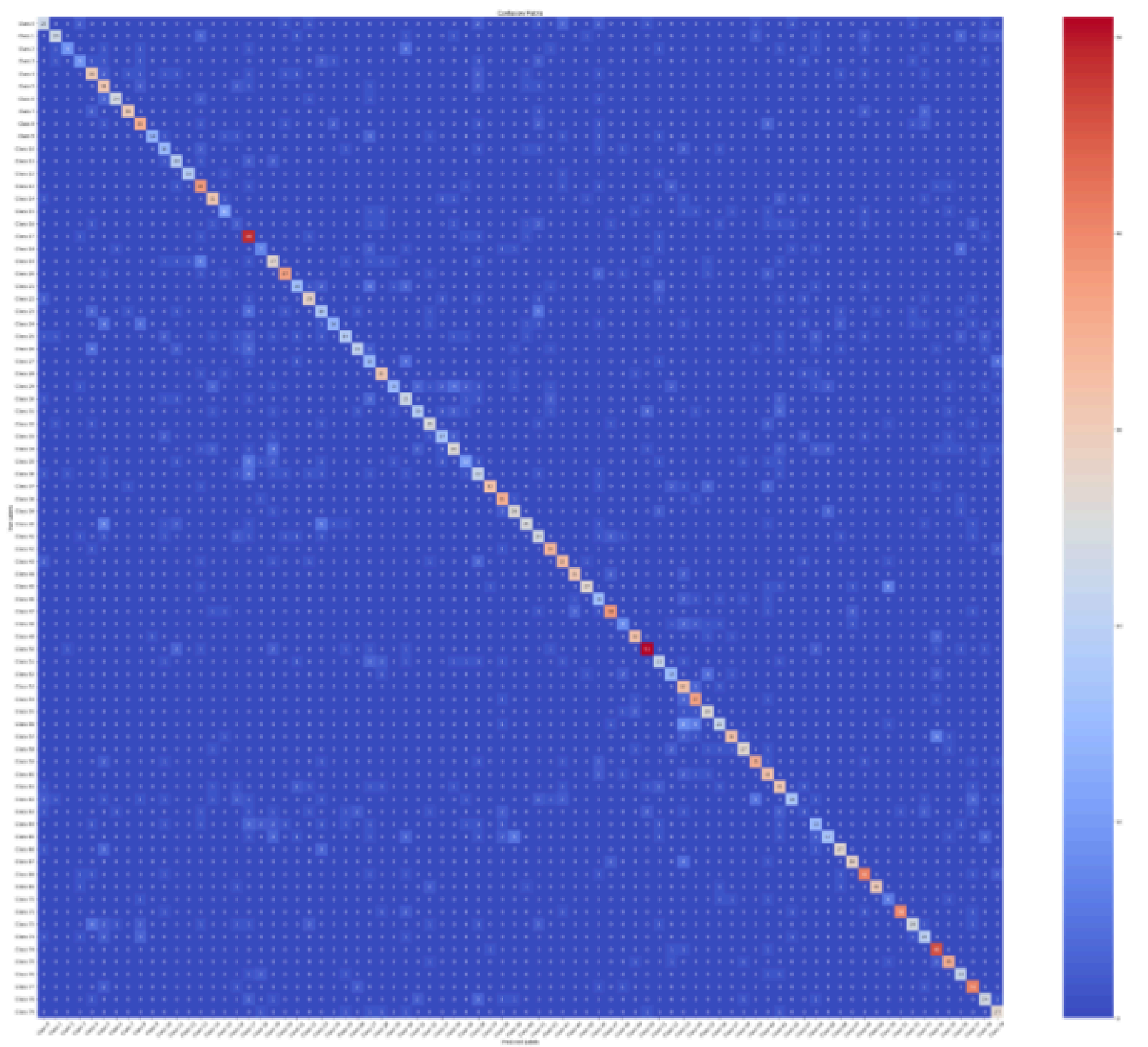
Results for ResNet

```
Accuracy: 60.98%
F1 Score: 0.6024
Precision: 0.6232
Recall: 0.6098
```

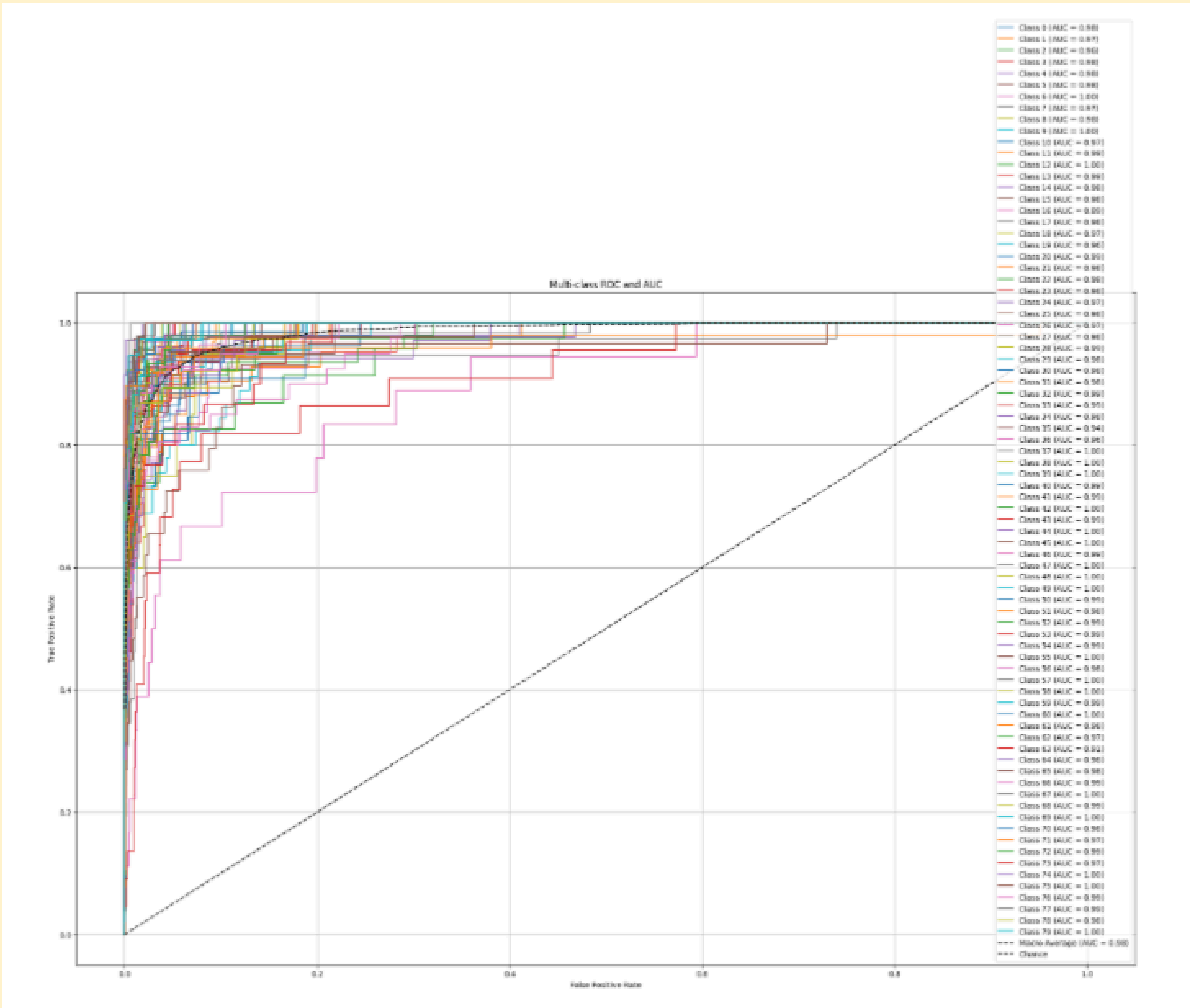
loss curve with visualization



confusion matrix with visualization



ROC & AUC



References and Papers

Residual Networks (ResNet):**Kaiming He, et al., *Deep Residual Learning for Image Recognition*, CVPR 2016.** [**Paper Link**]

Bottleneck Architecture in ResNet:Ioffe and Szegedy, *Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift.*Paper Link
Adam Optimizer:Kingma and Ba, *Adam: A Method for Stochastic Optimization*.Paper Link
PyTorch Documentation (Link).

2) Xception Finetuning:

What is Xception?

Xception (Extreme Inception) is a deep convolutional neural network architecture introduced by François Chollet in the paper:

- "Xception: Deep Learning with Depthwise Separable Convolutions" (Paper Link).

Key Features of Xception:

- **Depthwise Separable Convolutions:** A more efficient way to learn spatial and channel-wise features.
- **Fully Convolutional Network**: Contains no dense layers in its base architecture.
- **Efficiency:** Demonstrates better accuracy and fewer parameters compared to Inception models.

1)Importing Libraries

In [1]:

```
import tensorflow as tf
from tensorflow.keras.applications import Xception
from tensorflow.keras import layers, Model
import os
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.metrics import roc_curve, auc, confusion_matrix, classification_report
from itertools import cycle
import math
import pandas as pd
```

Explanation:

- **TensorFlow and Keras** are used for deep learning model development.
- **`Xception`**: Pretrained Xception model for transfer learning.
- **`layers` and `Model`:** Utilities for building and customizing models.
- Libraries like **`seaborn`** and **`matplotlib`** are used for visualization, while `sklearn` handles performance metrics.

2) Parameters and Preprocessing

]:

```
# Set parameters
IMG_HEIGHT = 299
IMG_WIDTH = 299
BATCH_SIZE = 32
AUTO = tf.data.AUTOTUNE
```

Explanation:

- `299x299`: Default input size for Xception.
- **`BATCH_SIZE`**: Number of samples processed in each batch.
- **`AUTO`**: Optimizes data loading using TensorFlow's pipeline.

3)Image Preprocessing and Augmentation

```python
# Read and preprocess image
def process_path(file_path, label):
    img = tf.io.read_file(file_path)
    img = tf.image.decode_jpeg(img, channels=3)
    img = tf.image.resize(img, [IMG_HEIGHT, IMG_WIDTH])
    img = tf.cast(img, tf.float32)
    img = tf.keras.applications.xception.preprocess_input(img)
    return img, label

# Data augmentation
def augment(image, label):
    image = tf.image.random_flip_left_right(image)
    image = tf.image.random_flip_up_down(image)

    # Random brightness, saturation, and contrast
    image = tf.image.random_brightness(image, 0.2)
    image = tf.image.random_saturation(image, 0.5, 2.0)
    image = tf.image.random_contrast(image, 0.5, 2.0)

    # Random crop and resize
    image = tf.image.random_crop(image, [IMG_HEIGHT-30, IMG_WIDTH-30, 3])
    image = tf.image.resize(image, [IMG_HEIGHT, IMG_WIDTH])

    return image, label
```

Explanation:

- **`process_path`**: Standardizes images to `299x299` and applies Xception-specific preprocessing.
- **`augment`**: Randomly alters images to improve model generalization.

4)Create Dataset

```python
    # Create lists of paths and labels
    image_paths = []
    labels = []

    for class_name in class_names:
        class_path = os.path.join(directory, class_name)
        for img_name in os.listdir(class_path):
            if img_name.lower().endswith(('.png', '.jpg', '.jpeg')):
                img_path = os.path.join(class_path, img_name)
                image_paths.append(img_path)
                labels.append(class_dict[class_name])

    # Create tf.data.Dataset
    ds = tf.data.Dataset.from_tensor_slices((image_paths, labels))

    # Shuffle if training
    if is_training:
        ds = ds.shuffle(len(image_paths), reshuffle_each_iteration=True)

    # Map preprocessing function
    ds = ds.map(process_path, num_parallel_calls=AUTO)

    # Apply augmentation if training
    if is_training:
        ds = ds.map(augment, num_parallel_calls=AUTO)

    # Batch and prefetch
    ds = ds.batch(BATCH_SIZE)
    ds = ds.prefetch(AUTO)

    return ds, len(image_paths)
```

Why?

- Efficiently loads, preprocesses, and augments images, reducing bottlenecks during training.

5)Model Definition

Load Pretrained Xception

```python
def create_model():
    # Base model
    base_model = Xception(weights=xception_weights, include_top=False, input_shape=(IMG_HEIGHT, I
MG_WIDTH, 3))
    base_model.trainable = False
```

Why?

- **`include_top=False`**: Removes the classification head for fine-tuning.
- **`trainable=False`**: Freezes weights to preserve pretrained knowledge.

Add Custom Layers

```python
    # Add custom layers
    x = layers.GlobalAveragePooling2D()(x)
    x = layers.BatchNormalization()(x)

    # Dense layers with regularization
    x = layers.Dense(1024, kernel_regularizer=tf.keras.regularizers.l2(1e-4))(x)
    x = layers.BatchNormalization()(x)
    x = layers.Activation('relu')(x)
    x = layers.Dropout(0.3)(x)

    x = layers.Dense(512, kernel_regularizer=tf.keras.regularizers.l2(1e-4))(x)
    x = layers.BatchNormalization()(x)
    x = layers.Activation('relu')(x)
    x = layers.Dropout(0.3)(x)

    outputs = layers.Dense(NUM_CLASSES, activation='softmax')(x)

    return Model(inputs, outputs)
```

Explanation:

- GlobalAveragePooling2D: Reduces spatial dimensions to a vector.
- Dense layers: Learn task-specific features.
- Dropout: Mitigates overfitting.

6)Training the Model

In [10]:

```
# Create model
model = create_model()

# Compile model
initial_learning_rate = 1e-3
optimizer = tf.keras.optimizers.Adam(learning_rate=initial_learning_rate)

model.compile(optimizer=optimizer, loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Callbacks
callbacks = [
    tf.keras.callbacks.ModelCheckpoint('best_model.keras', save_best_only=True, monitor='val_accu
racy'),
    tf.keras.callbacks.EarlyStopping(monitor='val_accuracy', patience=5, restore_best_weights=Tru
e),
    tf.keras.callbacks.ReduceLROnPlateau(monitor='val_accuracy', factor=0.2, patience=3, min_lr=1
e-6)
            ]
```

Train the model with 10 epochs

In [11]:

```
# First training phase
print("Phase 1: Training top layers...")
history1 = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=10,
    callbacks=callbacks
)
```

Finetune it with 15 epochs

n [12]:

```
# Fine-tuning phase
print("Phase 2: Fine-tuning Xception layers...")
base_model = model.layers[1]
base_model.trainable = True

# Recompile with lower learning rate
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=1e-5), loss='sparse_categorical_cr
ossentropy', metrics=['accuracy'])

history2 = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=15,
    callbacks=callbacks
)
```

Adam Optimizer: Efficient gradient descent with adaptive learning rates.
Loss Function: Suitable for multi-class classification.

Why?

- Initial training focuses on top layers.
- Fine-tuning adjusts pretrained layers for the dataset.

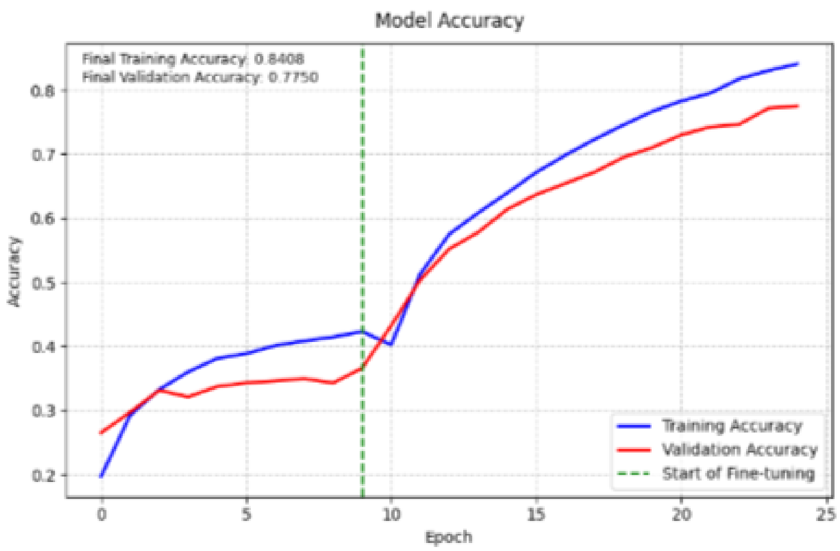
Results for Xception

Accuracy

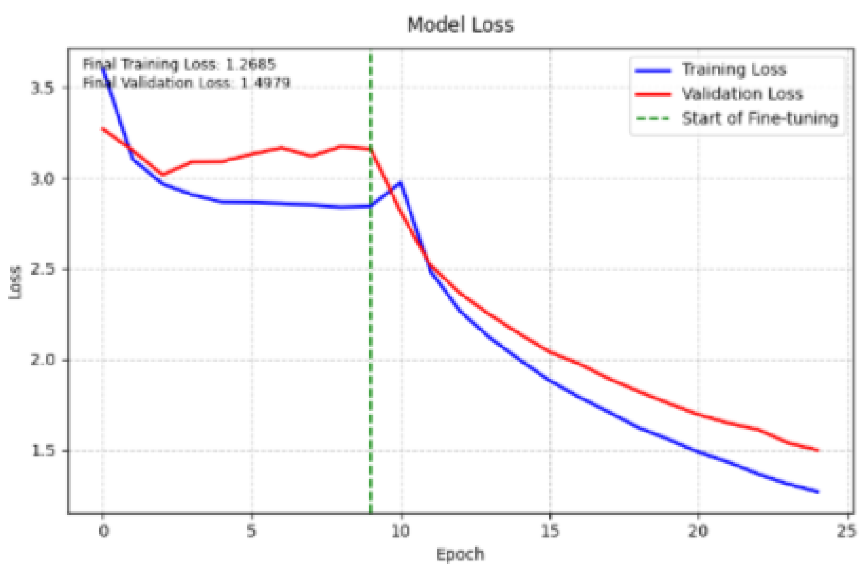
Training Accuracy: 0.8408

Validation Accuracy: 0.7750

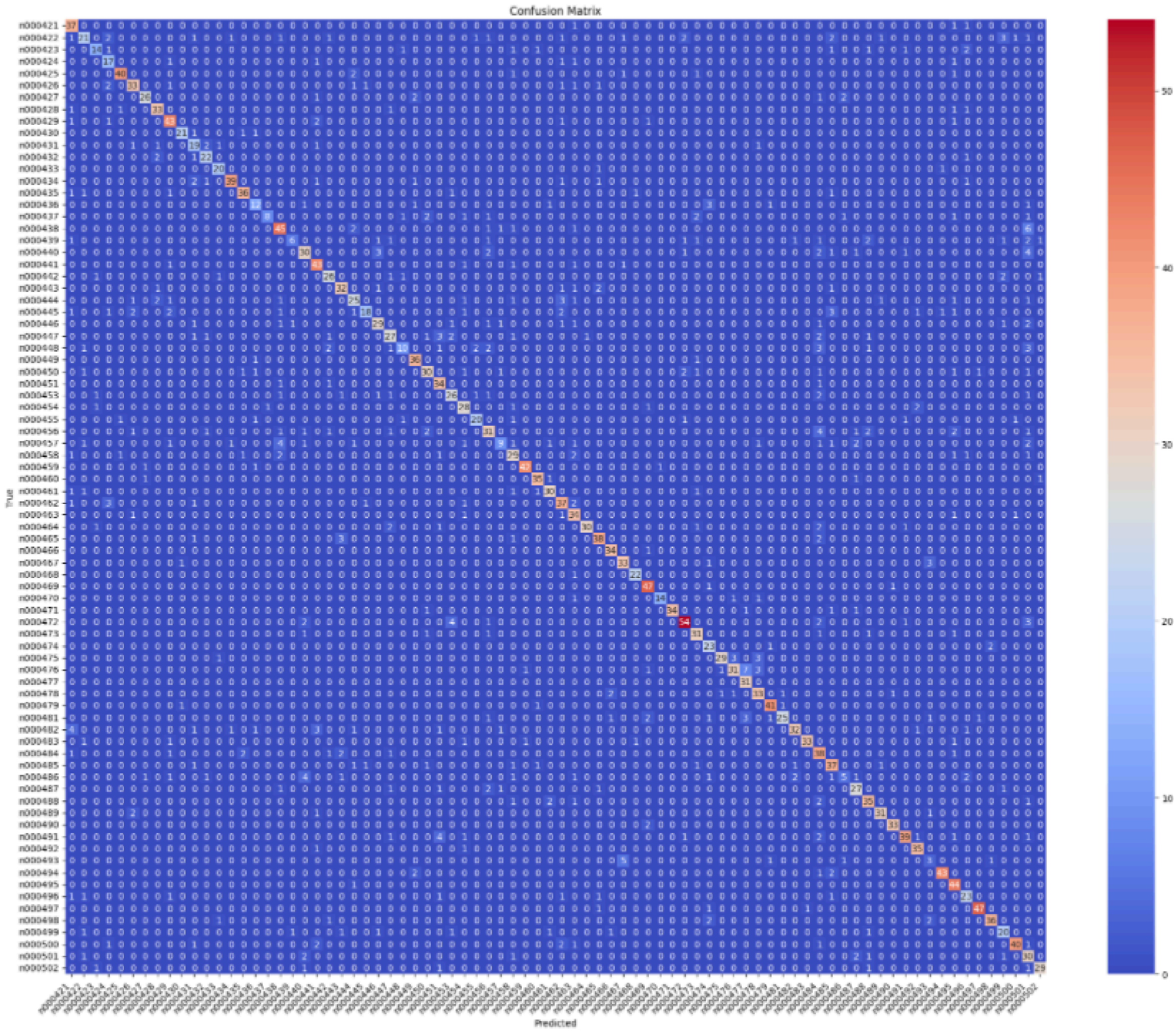
Accuracy with visualization



Loss curve with visualization



confusion matrix with visualization



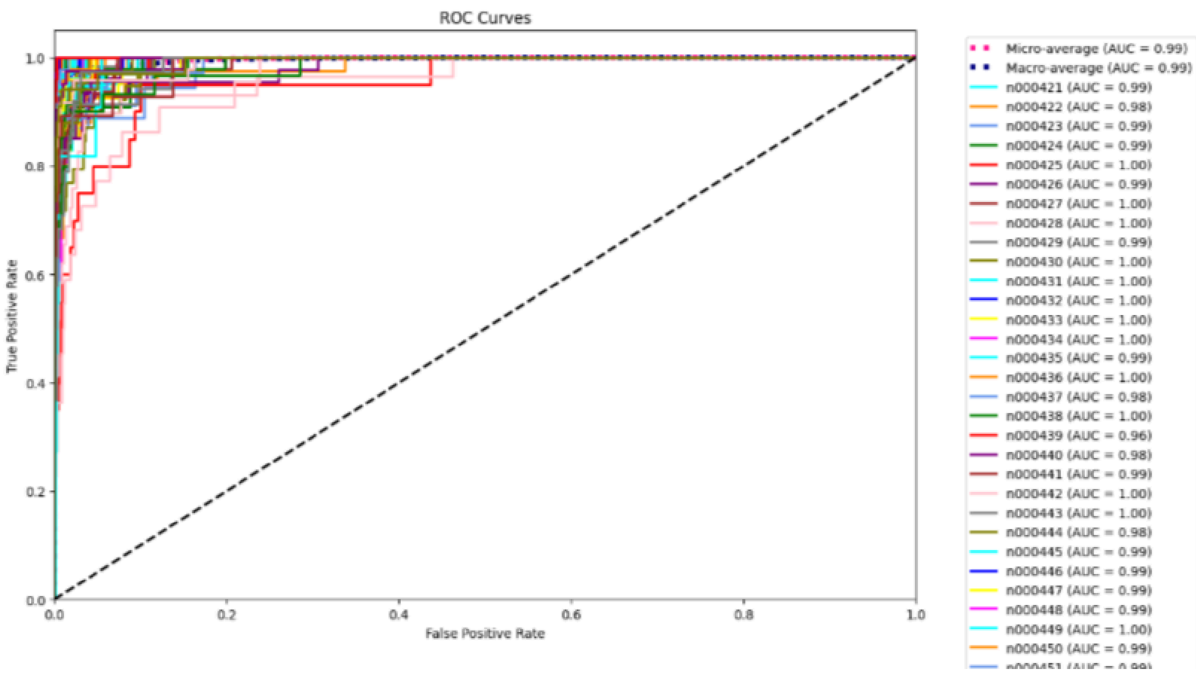
Recall, Precision and f-score

Average Metrics:

===============

	Precision	Recall	F1-Score
Macro Average	0.794687	0.777405	0.777017
Weighted Average	0.804026	0.794820	0.792012

ROC, AUC graph



References and Papers:-

Original Paper:[Xception: Deep Learning with Depthwise Separable Convolutions](#) (François Chollet, 2017).

3) DenseNet Finetuning:

What is DenseNet?

DenseNet, short for Dense Convolutional Network, was introduced in the paper: "Densely Connected Convolutional Networks" by Gao Huang et al. [(Paper Link)].

Key Features:

1. **Dense Connections:**
    - **Every layer is connected to all subsequent layers, ensuring maximum feature reuse.**
    - **This reduces redundancy and improves gradient flow.**
2. **Parameter Efficiency:**
    - **Since layers reuse features, DenseNet requires fewer parameters compared to traditional CNNs.**
3. **Benefits:**
    - **Reduces the vanishing gradient problem.**
    - **Reduces overfitting by promoting feature reuse.**
    - **Requires fewer parameters and computations compared to ResNet.**

1)Importing Libraries

In [3]:

```
import tensorflow as tf
from tensorflow.keras.applications import DenseNet121
from tensorflow.keras import layers, Model
import os
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.metrics import roc_curve, auc, confusion_matrix, classification_report
from itertools import cycle
import math
import pandas as pd
```

Explanation:

- `DenseNet121`: Loads a pretrained DenseNet-121 model from `keras.applications`.
- `seaborn`/`matplotlib`: Used for visualizing metrics such as confusion matrix and ROC curve.
- `sklearn.metrics`: For evaluating classification performance.

2) Parameters and Preprocessing

In [4]:

```
# Set parameters
IMG_HEIGHT = 224  # DenseNet121 default input size
IMG_WIDTH = 224
BATCH_SIZE = 32
AUTO = tf.data.AUTOTUNE

# Get number of classes
NUM_CLASSES = len(os.listdir(train_dir))
print(f"Number of classes: {NUM_CLASSES}")
```

Explanation:

- `IMG_HEIGHT`, `IMG_WIDTH`: Set to 224x224, DenseNet-121's expected input size.
- `BATCH_SIZE`: Determines the number of images per training step.
- `NUM_CLASSES`: Calculates the number of classes based on subdirectories in the dataset.

3. Preprocessing Functions

a. Image Loading

In [5]:

```
def process_path(file_path, label):
    # Read and preprocess image
    img = tf.io.read_file(file_path)
    img = tf.image.decode_jpeg(img, channels=3)
    img = tf.image.resize(img, [IMG_HEIGHT, IMG_WIDTH])
    img = tf.cast(img, tf.float32)
    # Preprocess for DenseNet
    img = tf.keras.applications.densenet.preprocess_input(img)
    return img, label
```

Explanation:

- Loads and decodes the image.
- Resizes it to the required dimensions (224x224).
- Applies DenseNet's preprocessing (`subtracts mean pixel value, divides by standard deviation`).

b. Data Augmentation

```
def augment(image, label):
    # Data augmentation
    image = tf.image.random_flip_left_right(image)
    image = tf.image.random_flip_up_down(image)

    # Random brightness, contrast, and saturation
    image = tf.image.random_brightness(image, 0.2)
    image = tf.image.random_saturation(image, 0.5, 2.0)
    image = tf.image.random_contrast(image, 0.5, 2.0)

    return image, label
```

Explanation:

- Random transformations improve model robustness by simulating variations in data (e.g., flipped or brighter images).

4. Dataset Creation

```
def create_dataset(directory, is_training=False):
    class_names = sorted(os.listdir(directory))
    class_dict = {name: idx for idx, name in enumerate(class_names)}

    image_paths = []
    labels = []

    for class_name in class_names:
        class_path = os.path.join(directory, class_name)
        for img_name in os.listdir(class_path):
            if img_name.lower().endswith(('.png', '.jpg', '.jpeg')):
                img_path = os.path.join(class_path, img_name)
                image_paths.append(img_path)
                labels.append(class_dict[class_name])

    ds = tf.data.Dataset.from_tensor_slices((image_paths, labels))

    if is_training:
        ds = ds.shuffle(len(image_paths), reshuffle_each_iteration=True)

    ds = ds.map(process_path, num_parallel_calls=AUTO)

    if is_training:
        ds = ds.map(augment, num_parallel_calls=AUTO)

    ds = ds.batch(BATCH_SIZE)
    ds = ds.prefetch(AUTO)

    return ds, len(image_paths)
```

Explanation:

- Loads image paths and labels.
- Applies preprocessing and augmentation (only for training data).
- **Prefetching**: Ensures data loading does not become a bottleneck.

Benefits of Prefetching:

1. **Overlapping Data Preparation and Computation**:
   - Prefetching allows the pipeline to prepare the next batch of data **while** the current batch is being used for training.
   - This overlap minimizes idle time for the training hardware.
2. **Efficiency**:
   - Data is prepared ahead of time and readily available when required.
   - For large datasets, this can significantly reduce training time.
3. **Seamless Pipeline**:
   - By ensuring a constant flow of data to the GPU/CPU, prefetching maintains smooth training execution.

5. Model Creation

In [7]:
```
def create_model():
    # Load pre-trained DenseNet121
    base_model = DenseNet121(
        weights='imagenet',
        include_top=False,
        input_shape=(IMG_HEIGHT, IMG_WIDTH, 3)
    )

    # Freeze the base model
    base_model.trainable = False

    # Create model
    inputs = tf.keras.Input(shape=(IMG_HEIGHT, IMG_WIDTH, 3))
    x = base_model(inputs, training=False)

    # Add custom layers
    x = layers.GlobalAveragePooling2D()(x)
    x = layers.BatchNormalization()(x)

    # Dense layers
    x = layers.Dense(1024, kernel_regularizer=tf.keras.regularizers.l2(1e-4))(x)
    x = layers.BatchNormalization()(x)
    x = layers.Activation('relu')(x)
    x = layers.Dropout(0.5)(x)

    x = layers.Dense(512, kernel_regularizer=tf.keras.regularizers.l2(1e-4))(x)
    x = layers.BatchNormalization()(x)
    x = layers.Activation('relu')(x)
    x = layers.Dropout(0.5)(x)

    # Output layer
    outputs = layers.Dense(NUM_CLASSES, activation='softmax')(x)

    return Model(inputs, outputs)
```

Explanation:

1. DenseNet121 Base:
   - `weights='imagenet'`: Loads pretrained weights from ImageNet.
   - `include_top=False`: Removes the final classification layers, allowing custom layers.
   - Why DenseNet121? Efficient parameter usage, strong feature reuse, and high accuracy.
2. Custom Head:
   - `GlobalAveragePooling2D`: Reduces spatial dimensions to 1x1 while retaining features
   - Dense layers with Batch Normalization, ReLU activation, Dropout, and L2 Regularization to prevent overfitting.
   - Output layer uses softmax for multiclass classification.

6. Training

Phase 1: Training Only Custom Layers

```
print("Phase 1: Training top layers...")
history1 = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=10,
    callbacks=callbacks
)
```

Initial Phase: Only the custom layers are trained while the DenseNet base remains frozen.

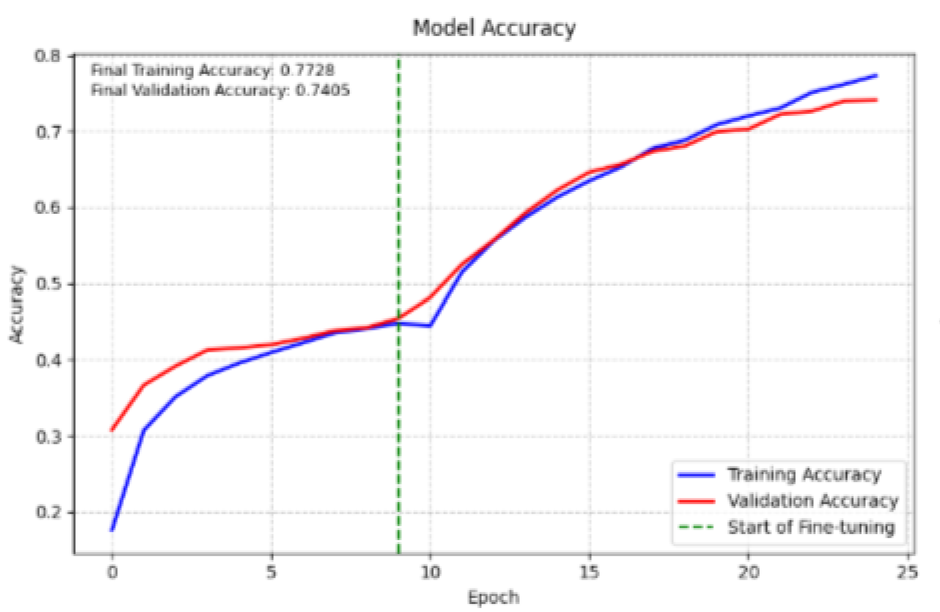
Phase 2: Fine-Tuning

```
base_model.trainable = True

# Freeze first 100 layers of DenseNet
for layer in base_model.layers[:100]:
    layer.trainable = False

# Recompile with lower learning rate
model.compile(
    optimizer=tf.keras.optimizers.Adam(
        learning_rate=1e-5,
        weight_decay=1e-6
    ),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)

# Second training phase
history2 = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=15,
    callbacks=callbacks
)
```

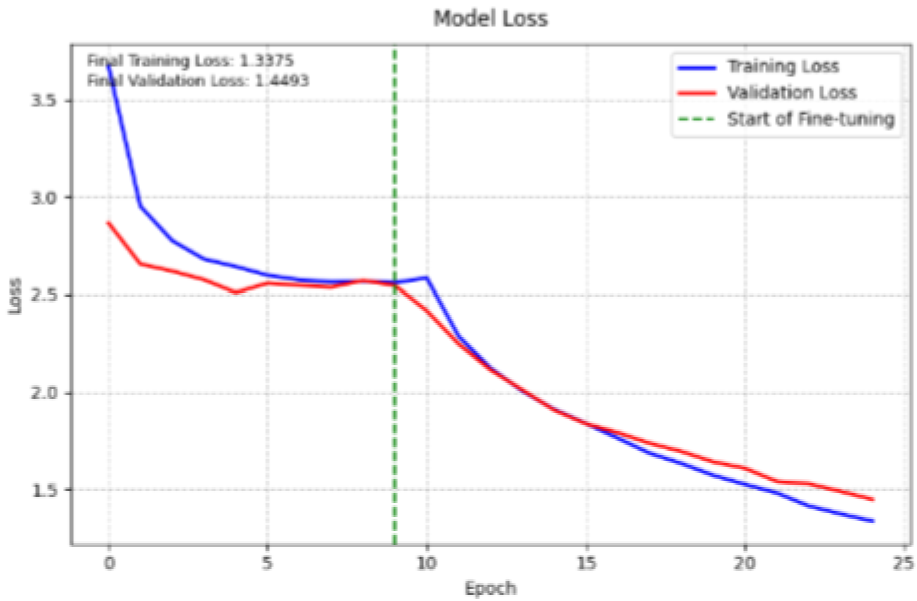
Fine-Tuning: Allows selected DenseNet layers to be trainable while freezing earlier layers to retain pretrained features.

Results for DenseNet

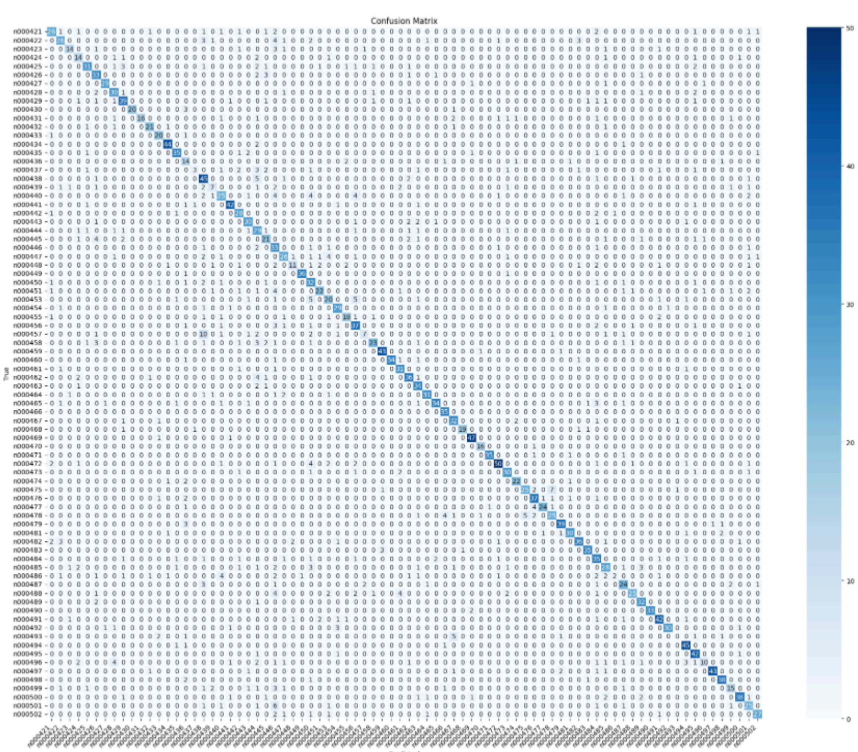
accuracy with visualization



loss curve with visualization



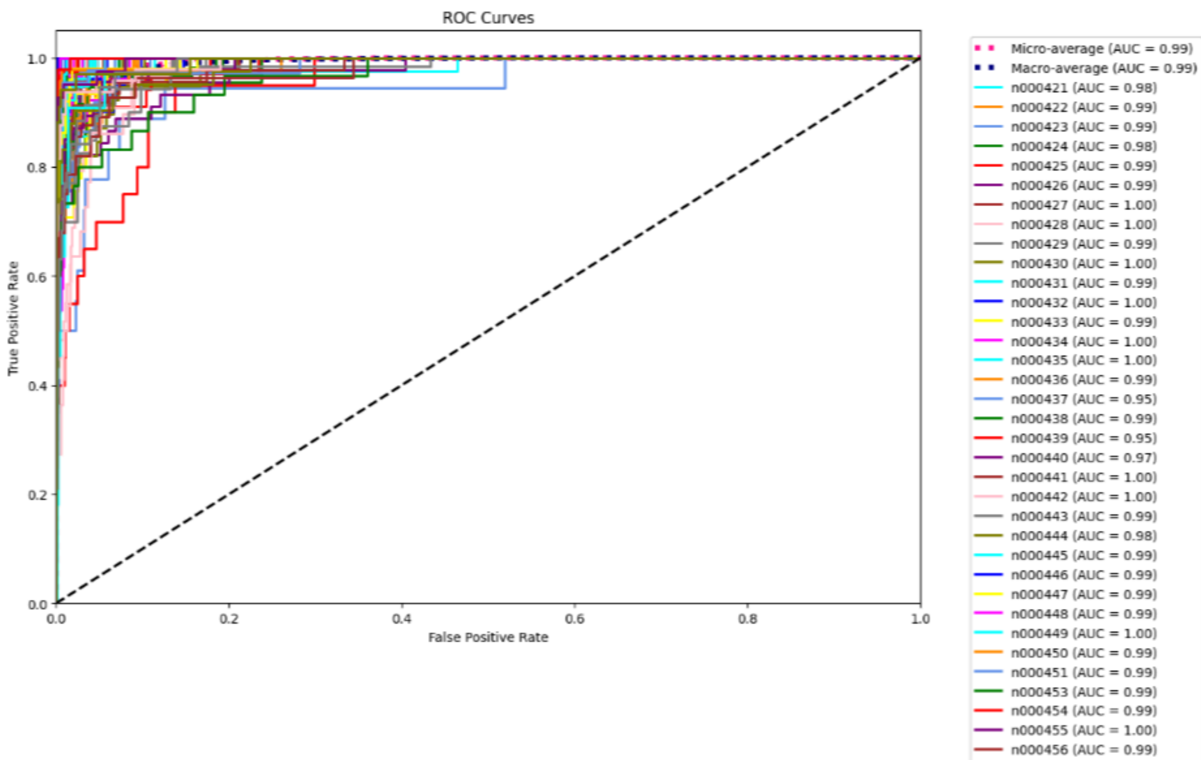
confusion matrix with visualization



recall, precision, f-score

```
Average Metrics:
================
                  Precision    Recall  F1-Score
Macro Average      0.762601  0.734106  0.734552
Weighted Average   0.772903  0.756811  0.753750
```

ROC & AUC



Accuracy

```
Training Accuracy: 0.7728
Validation Accuracy: 0.7405
```

References and Papers:-

DenseNet Paper: Gao Huang, et al., *Densely Connected Convolutional Networks*.[Paper Link]

Comparison of ResNet, DenseNet, and Xception for Celebrity Face Classification

Results and Performance Summary

Model	Accuracy	Key Features	Inference speed	Parameter Efficiency	Ease of Training
ResNet	60.98%	Residual connections mitigate vanishing gradients and allow deep architectures.	Moderate	Moderate	Easy
DenseNet	74.05%	Dense connections maximize feature reuse and improve gradient flow.	Slow	High (Low Redundancy)	Moderate
Xception	**77.50%**	Depthwise separable convolutions for computational efficiency and strong feature extraction.	Fast	Moderate	Moderate

Pros and Cons of Each Architecture

1)ResNet

- **Pros:**
    1. **Residual Connections**: Enables effective training of very deep networks by bypassing layers through identity mappings.
    2. **Simplifies Optimization**: The network learns residual mappings (differences) instead of full transformations, reducing the risk of overfitting.
    3. **Well-suited for General Tasks**: A robust architecture that performs well on a variety of image classification tasks.

4. **Scalability**: Can be scaled to very deep architectures like ResNet-101 or ResNet-152.

- **Cons**:
  1. **Parameter Redundancy**: Requires more parameters compared to DenseNet due to lack of feature reuse across layers.
  2. **Moderate Computational Demand**: Although residual connections improve training, the architecture is not as parameter-efficient as DenseNet.

---

2)DenseNet

- **Pros**:
  1. **Feature Reuse**: Dense connections ensure all layers can access features from preceding layers, improving efficiency.
  2. **Parameter Efficiency**: Requires fewer parameters by reusing features and avoiding redundant calculations.
  3. **Gradient Flow**: Alleviates vanishing gradients due to dense connections.
- **Cons**:
  1. **Inference Speed**: Dense connections increase memory and computational overhead during inference.
  2. **Training Complexity**: Can be harder to train due to potential overfitting from over-reliance on feature reuse.

---

3)Xception

- **Pros:**
    1. **Depthwise Separable Convolutions**: Reduces computational complexity by decoupling spatial and depthwise convolutions.
    2. **Strong Feature Extraction**: Excels in learning hierarchical features, making it suitable for complex tasks like facial recognition.
    3. **Parameter Efficiency**: Balances between DenseNet and ResNet in terms of parameter requirements.
    4. **Faster Inference**: Depthwise separable convolutions improve speed without compromising accuracy.
- **Cons:**
    1. **Moderate Training Complexity**: Requires careful adjustment of hyperparameters to avoid overfitting.
    2. **Not Fully Generalized**: While it excels in specific tasks, it may not always outperform traditional architectures on simpler datasets.

Analysis and Recommendation for Celebrity Face Classification

Dataset Characteristics:

1. **High Variability**: Celebrity datasets typically have diverse lighting, expressions, and occlusions.
2. **Relatively Small Number of Samples per Class**: Demands strong feature extraction to handle overfitting.
3. **Task Complexity**: Requires learning subtle differences between faces.

Best Model for the Task: Xception

- **Reasons:**
  1. **Higher Accuracy**: Xception achieves 77.50% accuracy, outperforming ResNet and DenseNet on this dataset.
  2. **Feature Extraction**: Depthwise separable convolutions allow efficient extraction of spatial hierarchies, crucial for distinguishing fine details in celebrity faces.
  3. **Inference Speed**: Faster inference with a comparable number of parameters makes it suitable for real-world applications like facial recognition systems.
  4. **Generalization**: Excels in handling datasets with variability in facial attributes, as observed from its superior validation performance.

Conclusion

For celebrity face classification:

1. **Xception** is the most suitable due to its accuracy and computational efficiency.
2. **DenseNet** is a close contender but struggles with inference speed and overfitting on small datasets.
3. **ResNet** provides robust performance but lacks the parameter efficiency and advanced feature extraction capabilities of the other models.

References and papers for all documentation:

DenseNet (Densely Connected Convolutional Networks)

1. **Original Paper:**

- Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). *Densely Connected Convolutional Networks*. ArXiv Link

2. **Github Implementations:**
   - DenseNet PyTorch Implementation Link

Xception (Extreme Inception)

1. **Original Paper:**
   - Chollet, F. (2016). *Xception: Deep Learning with Depthwise Separable Convolutions*. ArXiv Link
2. **Github Implementations:**
   - Xception TensorFlow Implementation Link

General Resources

1. **Transfer Learning in Keras:**
   - Official Documentation:Link
2. **ImageNet Dataset for Pretraining:**
   - ImageNet Official Website: Link
3. **Visualization Tools:**
   - TensorFlow documentation: Link
   - Grad-CAM for Model Explainability: Link

This project applied by :

Farida Khaled Madiha Saeed Mohammed Tarek
Hanya Ruby Esraa Ammar Mohammed Yasser

Our repo on Github

https://github.com/Farida-EL-Shenawy/Neural-networks-and-Deep-learning-models