Noah Anderson

July 15th, 2024

Load Libraries

In [ ]:
```
from efficientnet_pytorch import EfficientNet
from torchvision import  transforms
from torchvision.datasets import ImageFolder
from torch.utils.data.dataloader import DataLoader
import os
import torch
from torch.optim.lr_scheduler import ReduceLROnPlateau
import multiprocessing
from torch.utils.data import DataLoader, ConcatDataset, random_split
import numpy as np
import torch
from torchvision.transforms import Compose, RandomRotation, RandomHorizontalFlip, Resize, CenterCrop, ToTe
from PIL import Image
import torch
from sklearn.metrics import precision_score, recall_score, f1_score
```

Define Transformations and Read Data

In [ ]:
```
# Center crop and resize to 224 by 224 and convert to tensor
data_transform = Compose([
    Resize(224),
    CenterCrop(224),
    ToTensor()
])

# Define data path
data_dir = "mendeley_data"

# Read in the data with ImageFolder
data = ImageFolder(data_dir, transform = data_transform)
```

Shuffling and Re-Splitting Test and Train

In [ ]:
```
# Set seed for reproducibility
torch.manual_seed(42)  # You can use any integer value as the seed

# Define the sizes for the splits
train_size = int(0.8 * len(data))
val_size = int(0.1 * len(data))
test_size = len(data) - train_size - val_size

# Split the dataset into new train and test sets (e.g., 90% train, 10% test)
trainset, valset, testset = random_split(data, [train_size, val_size, test_size])

# Define batchsize
batch_size = 32

# DataLoaders
train_loader = DataLoader(trainset, batch_size = batch_size, shuffle = True, num_workers = 6, pin_memory =
val_loader = DataLoader(valset, batch_size = batch_size * 2, shuffle = True, num_workers = 6, pin_memory =
test_loader = DataLoader(testset, batch_size = batch_size * 2, num_workers = 6, pin_memory = True)
```

Change Device to GPU

In [ ]:
```
# Set device to CPU
device = torch.device("mps") # try runnign mps next
print(f'Using device: {device}')

multiprocessing.set_start_method("fork")
```

```
Using device: mps
```

Set Model Features

In [ ]:
```
# Load the pre-trained EfficientNet-B0 model
model = EfficientNet.from_pretrained('efficientnet-b0')
```

```
# Modify the last layer to match the number of classes in your dataset
num_classes = len(data.classes)
model._fc = torch.nn.Linear(model._fc.in_features, num_classes)


# Move model to the device (CPU in this case)
model.to(device)

# Define loss function and optimizer
criterion = torch.nn.CrossEntropyLoss()

# Select Adam optimizer
optimizer = torch.optim.Adam(model.parameters(), lr = .001) # Learning rate used in Kaur et. al

# Learning Rate Scheduler
scheduler = ReduceLROnPlateau(optimizer, mode = 'max', factor = 0.3, patience = 2)

# Define accuracy function
def calculate_accuracy(outputs, labels):
    _, preds = torch.max(outputs, 1)
    corrects = (preds == labels).sum().item()
    return corrects
```

```
Loaded pretrained weights for efficientnet-b0
```

Train Model

In [ ]:

```
# Set initial values for epoch tracking lists
train_losses = [] # Training loss list
val_losses = [] # Validation loss list
train_accuracies = [] # Training accuracy list
val_accuracies = [] # Validation accuracy list
num_epochs = 30 # Define number of epochs
min_valid_loss = np.inf # Initialize minimum validation loss as infinite
max_valid_accuracy = 0 # Initalize maximum validation accuracy as 0

# Epoch training loop
for epoch in range(num_epochs):
```

```
    model.train()  # Set the model to training mode
    train_loss = 0.0 # Initialize training loss
    running_corrects = 0

    for batch_images, batch_labels in train_loader:
        batch_images, batch_labels = batch_images.to(device), batch_labels.to(device)  # Move data to the (

        optimizer.zero_grad()  # Zero the gradients
        outputs = model(batch_images)  # Forward pass
        loss = criterion(outputs, batch_labels)  # Compute loss
        loss.backward()  # Backward pass
        optimizer.step()  # Update model parameters

        train_loss += loss.item() * batch_images.size(0)  # Accumulate loss
        running_corrects += calculate_accuracy(outputs, batch_labels)  # Accumulate correct predictions

    print("     Epoch training complete, now starting validation")

    ### Validation
    val_loss = 0.0
    val_corrects = 0
    model.eval()
    with torch.no_grad():  # Disable gradient calculation
        for batch_images, batch_labels in val_loader:
            batch_images, batch_labels = batch_images.to(device), batch_labels.to(device)  # Move data to 1

            outputs = model(batch_images)
            loss = criterion(outputs, batch_labels)
            val_loss += loss.item() * batch_images.size(0)  # Accumulate loss
            val_corrects += calculate_accuracy(outputs, batch_labels)  # Accumulate correct predictions

    train_loss /= len(train_loader.dataset)
    val_loss /= len(val_loader.dataset)
    train_acc = running_corrects / len(train_loader.dataset)
    val_acc = val_corrects / len(val_loader.dataset)

    print(f'Epoch {epoch + 1} \t\t Training Loss: {train_loss:.4f} \t\t Validation Loss: {val_loss:.4f} \t\

    train_losses.append(train_loss)
    val_losses.append(val_loss)
    train_accuracies.append(train_acc)
    val_accuracies.append(val_acc)
```

```
    if min_valid_loss > val_loss:
        print(f'Validation loss decreased({min_valid_loss:.6f}--->{val_loss:.6f}) \t Saving the model')
        min_valid_loss = val_loss
        torch.save(model.state_dict(), 'saved_models/saved_model.pth')

    if val_acc > max_valid_accuracy:
        print(f'Validation accuracy increased ({max_valid_accuracy:.6f})--->{val_acc} \t Saving the best ac
        max_valid_accuracy = val_acc
        torch.save(model.state_dict(), 'saved_models/best_accuracy_model.pth')

    scheduler.step(val_loss)
```

```
     Epoch training complete, now starting validation
Epoch 1                  Training Loss: 0.1921          Validation Loss: 1.8668                 Training A
ccuracy: 0.9379                  Validation Accuracy: 0.5541
Validation loss decreased(inf--->1.866763)       Saving the model
Validation accuracy increased (0.000000)--->0.5541310541310541   Saving the best accuracy model
     Epoch training complete, now starting validation
Epoch 2                  Training Loss: 0.0729          Validation Loss: 0.1751                 Training A
ccuracy: 0.9753                  Validation Accuracy: 0.9345
Validation loss decreased(1.866763--->0.175090)          Saving the model
Validation accuracy increased (0.554131)--->0.9344729344729344   Saving the best accuracy model
     Epoch training complete, now starting validation
Epoch 3                  Training Loss: 0.0607          Validation Loss: 0.1441                 Training A
ccuracy: 0.9810                  Validation Accuracy: 0.9387
Validation loss decreased(0.175090--->0.144060)          Saving the model
Validation accuracy increased (0.934473)--->0.9387464387464387   Saving the best accuracy model
     Epoch training complete, now starting validation
Epoch 4                  Training Loss: 0.0359          Validation Loss: 0.2163                 Training A
ccuracy: 0.9897                  Validation Accuracy: 0.9416
Validation accuracy increased (0.938746)--->0.9415954415954416   Saving the best accuracy model
     Epoch training complete, now starting validation
Epoch 5                  Training Loss: 0.0134          Validation Loss: 0.0208                 Training A
ccuracy: 0.9959                  Validation Accuracy: 0.9972
Validation loss decreased(0.144060--->0.020772)          Saving the model
Validation accuracy increased (0.941595)--->0.9971509971509972   Saving the best accuracy model
     Epoch training complete, now starting validation
Epoch 6                  Training Loss: 0.0048          Validation Loss: 0.0236                 Training A
ccuracy: 0.9989                  Validation Accuracy: 0.9900
     Epoch training complete, now starting validation
Epoch 7                  Training Loss: 0.0045          Validation Loss: 0.0241                 Training A
ccuracy: 0.9989                  Validation Accuracy: 0.9886
     Epoch training complete, now starting validation
Epoch 8                  Training Loss: 0.0023          Validation Loss: 0.0195                 Training A
ccuracy: 0.9995                  Validation Accuracy: 0.9943
Validation loss decreased(0.020772--->0.019507)          Saving the model
     Epoch training complete, now starting validation
Epoch 9                  Training Loss: 0.0016          Validation Loss: 0.0165                 Training A
ccuracy: 0.9996                  Validation Accuracy: 0.9929
Validation loss decreased(0.019507--->0.016507)          Saving the model
     Epoch training complete, now starting validation
Epoch 10                 Training Loss: 0.0017          Validation Loss: 0.0183                 Training A
ccuracy: 0.9998                  Validation Accuracy: 0.9943
     Epoch training complete, now starting validation
```

```
Epoch 11                Training Loss: 0.0025          Validation Loss: 0.0187                  Training A
ccuracy: 0.9995                   Validation Accuracy: 0.9943
     Epoch training complete, now starting validation
Epoch 12                Training Loss: 0.0019          Validation Loss: 0.0163                  Training A
ccuracy: 0.9996                   Validation Accuracy: 0.9929
Validation loss decreased(0.016507--->0.016280)          Saving the model
     Epoch training complete, now starting validation
Epoch 13                Training Loss: 0.0032          Validation Loss: 0.0221                  Training A
ccuracy: 0.9989                   Validation Accuracy: 0.9943
     Epoch training complete, now starting validation
Epoch 14                Training Loss: 0.0007          Validation Loss: 0.0207                  Training A
ccuracy: 1.0000                   Validation Accuracy: 0.9943
     Epoch training complete, now starting validation
Epoch 15                Training Loss: 0.0011          Validation Loss: 0.0204                  Training A
ccuracy: 1.0000                   Validation Accuracy: 0.9943
     Epoch training complete, now starting validation
Epoch 16                Training Loss: 0.0009          Validation Loss: 0.0196                  Training A
ccuracy: 1.0000                   Validation Accuracy: 0.9943
     Epoch training complete, now starting validation
Epoch 17                Training Loss: 0.0012          Validation Loss: 0.0192                  Training A
ccuracy: 0.9998                   Validation Accuracy: 0.9943
     Epoch training complete, now starting validation
Epoch 18                Training Loss: 0.0013          Validation Loss: 0.0196                  Training A
ccuracy: 0.9996                   Validation Accuracy: 0.9943
     Epoch training complete, now starting validation
Epoch 19                Training Loss: 0.0014          Validation Loss: 0.0199                  Training A
ccuracy: 0.9998                   Validation Accuracy: 0.9943
     Epoch training complete, now starting validation
Epoch 20                Training Loss: 0.0009          Validation Loss: 0.0196                  Training A
ccuracy: 1.0000                   Validation Accuracy: 0.9943
     Epoch training complete, now starting validation
Epoch 21                Training Loss: 0.0014          Validation Loss: 0.0194                  Training A
ccuracy: 0.9995                   Validation Accuracy: 0.9943
     Epoch training complete, now starting validation
Epoch 22                Training Loss: 0.0009          Validation Loss: 0.0199                  Training A
ccuracy: 1.0000                   Validation Accuracy: 0.9943
     Epoch training complete, now starting validation
Epoch 23                Training Loss: 0.0016          Validation Loss: 0.0195                  Training A
ccuracy: 0.9996                   Validation Accuracy: 0.9943
     Epoch training complete, now starting validation
Epoch 24                Training Loss: 0.0011          Validation Loss: 0.0198                  Training A
ccuracy: 0.9998                   Validation Accuracy: 0.9943
```

```
    Epoch training complete, now starting validation
Epoch 25            Training Loss: 0.0012        Validation Loss: 0.0193             Training A
ccuracy: 0.9995               Validation Accuracy: 0.9943
    Epoch training complete, now starting validation
Epoch 26            Training Loss: 0.0018        Validation Loss: 0.0203             Training A
ccuracy: 0.9996               Validation Accuracy: 0.9943
    Epoch training complete, now starting validation
Epoch 27            Training Loss: 0.0015        Validation Loss: 0.0199             Training A
ccuracy: 0.9996               Validation Accuracy: 0.9943
    Epoch training complete, now starting validation
Epoch 28            Training Loss: 0.0022        Validation Loss: 0.0193             Training A
ccuracy: 0.9993               Validation Accuracy: 0.9943
    Epoch training complete, now starting validation
Epoch 29            Training Loss: 0.0012        Validation Loss: 0.0195             Training A
ccuracy: 0.9996               Validation Accuracy: 0.9943
    Epoch training complete, now starting validation
Epoch 30            Training Loss: 0.0011        Validation Loss: 0.0203             Training A
ccuracy: 0.9998               Validation Accuracy: 0.9943
```

Test Model

Test model after all epochs

In [ ]:

```
model.eval()  # Set the model to evaluation mode
correct = 0
total = 0
predictions = []
true_labels = []

with torch.no_grad():
    for batch_images, batch_labels in test_loader:
        batch_images, batch_labels = batch_images.to(device), batch_labels.to(device)
        outputs = model(batch_images)
        _, predicted = torch.max(outputs, 1)

        predictions.extend(predicted.cpu().numpy())  # Convert predictions to CPU numpy array
        true_labels.extend(batch_labels.cpu().numpy())  # Convert true labels to CPU numpy array

        total += batch_labels.size(0)
```

```
        correct += (predicted == batch_labels).sum().item()

# Calculate accuracy
accuracy = 100 * correct / total
print(f'Validation Accuracy: {accuracy:.2f}%')

# Calculate precision score
precision = precision_score(true_labels, predictions, average='macro')
print(f'Precision Score: {precision:.4f}')

# Calculate recall score
recall = recall_score(true_labels, predictions, average='macro')
print(f'Recall Score: {recall:.4f}')

# Calculate F1 score
f1 = f1_score(true_labels, predictions, average='macro')
print(f'F1 Score: {f1:.4f}')
```

```
Validation Accuracy: 99.43%
Precision Score: 0.9948
Recall Score: 0.9942
F1 Score: 0.9945
```

Test model with the lowest validation loss

In [ ]:

```
model.load_state_dict(torch.load('saved_models/saved_model.pth'))


model.eval()  # Set the model to evaluation mode
correct = 0
total = 0
predictions = []
true_labels = []

with torch.no_grad():
    for batch_images, batch_labels in test_loader:
        batch_images, batch_labels = batch_images.to(device), batch_labels.to(device)
        outputs = model(batch_images)
        _, predicted = torch.max(outputs, 1)

        predictions.extend(predicted.cpu().numpy())  # Convert predictions to CPU numpy array
```

```
        true_labels.extend(batch_labels.cpu().numpy())  # Convert true labels to CPU numpy array

        total += batch_labels.size(0)
        correct += (predicted == batch_labels).sum().item()

# Calculate accuracy
accuracy = 100 * correct / total
print(f'Validation Accuracy: {accuracy:.2f}%')

# Calculate precision score
precision = precision_score(true_labels, predictions, average='macro')
print(f'Precision Score: {precision:.4f}')

# Calculate recall score
recall = recall_score(true_labels, predictions, average='macro')
print(f'Recall Score: {recall:.4f}')

# Calculate F1 score
f1 = f1_score(true_labels, predictions, average='macro')
print(f'F1 Score: {f1:.4f}')
```

```
Validation Accuracy: 99.29%
Precision Score: 0.9933
Recall Score: 0.9930
F1 Score: 0.9932
```

Test model with best validation accuracy

In [ ]:

```
model.load_state_dict(torch.load('saved_models/best_accuracy_model.pth'))

model.eval()  # Set the model to evaluation mode
correct = 0
total = 0
predictions = []
true_labels = []

with torch.no_grad():
    for batch_images, batch_labels in test_loader:
        batch_images, batch_labels = batch_images.to(device), batch_labels.to(device)
        outputs = model(batch_images)
        _, predicted = torch.max(outputs, 1)
```

```
        predictions.extend(predicted.cpu().numpy())  # Convert predictions to CPU numpy array
        true_labels.extend(batch_labels.cpu().numpy())  # Convert true labels to CPU numpy array

        total += batch_labels.size(0)
        correct += (predicted == batch_labels).sum().item()

# Calculate accuracy
accuracy = 100 * correct / total
print(f'Validation Accuracy: {accuracy:.2f}%')

# Calculate precision score
precision = precision_score(true_labels, predictions, average='macro')
print(f'Precision Score: {precision:.4f}')

# Calculate recall score
recall = recall_score(true_labels, predictions, average='macro')
print(f'Recall Score: {recall:.4f}')

# Calculate F1 score
f1 = f1_score(true_labels, predictions, average='macro')
print(f'F1 Score: {f1:.4f}')
```

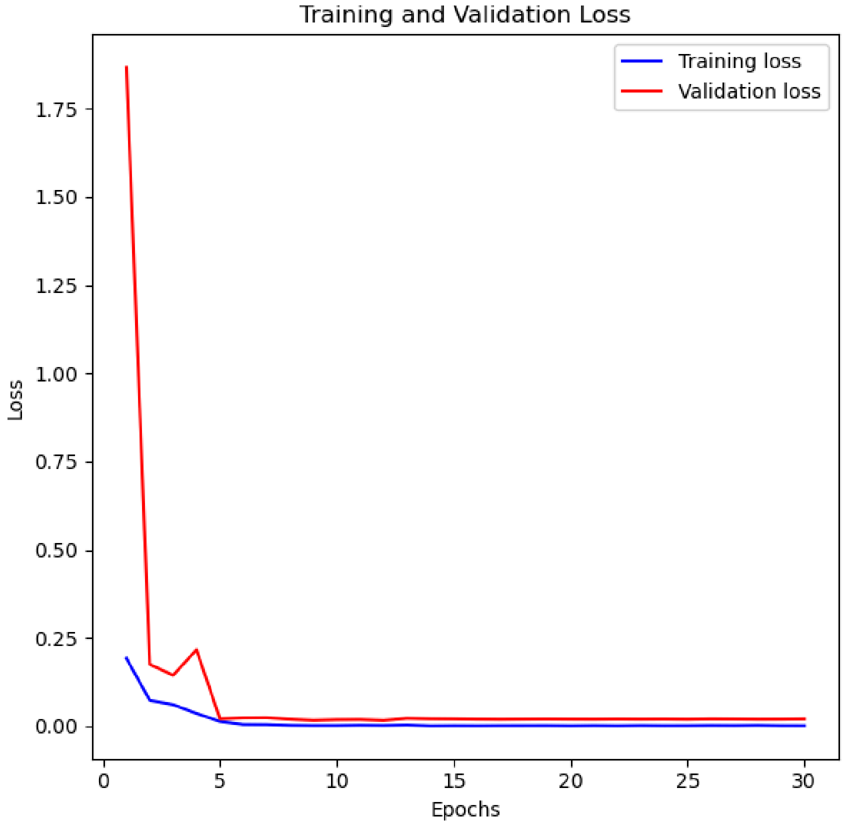
```
Validation Accuracy: 99.57%
Precision Score: 0.9960
Recall Score: 0.9957
F1 Score: 0.9959
```

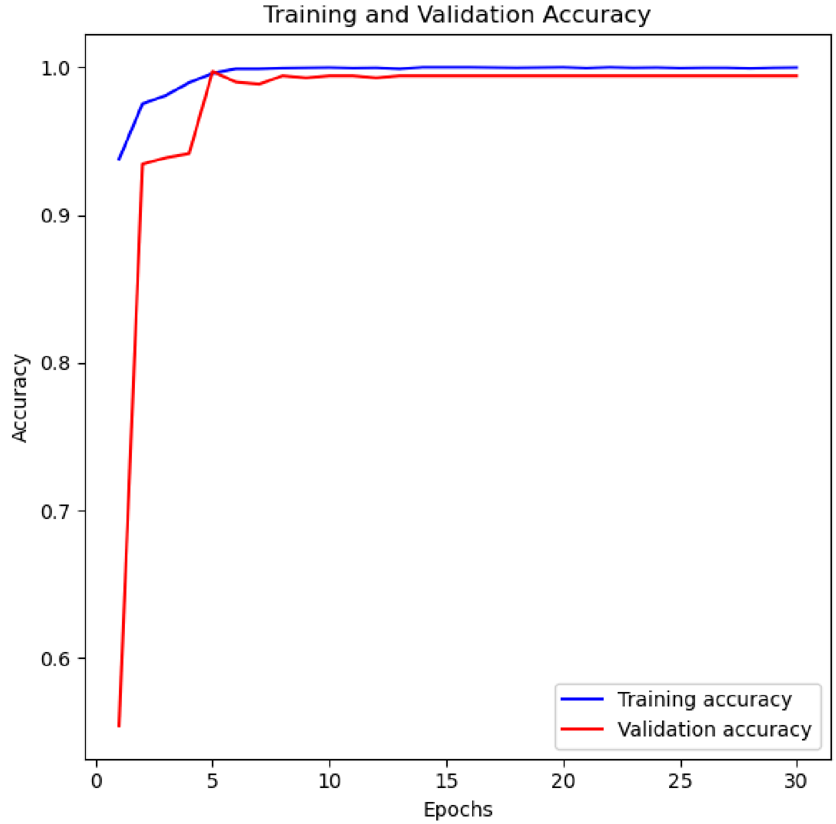
Plot Training and Validation and Loss and Accuracy

In [ ]:

```
import matplotlib.pyplot as plt

# Plotting loss
plt.figure(figsize=(12, 6))

epochs = range(1, len(train_losses) + 1)


plt.subplot(1, 2, 1)
plt.plot(epochs, train_losses, 'b', label='Training loss')
```

```
plt.plot(epochs, val_losses, 'r', label='Validation loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Plotting accuracy
plt.subplot(1, 2, 2)
plt.plot(epochs, train_accuracies, 'b', label='Training accuracy')
plt.plot(epochs, val_accuracies, 'r', label='Validation accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```


Training and Validation Loss
Training loss
Validation loss
Loss
Epochs
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
0
5
10
15
20
25
30


Training and Validation Accuracy
Training accuracy
Validation accuracy
Accuracy
Epochs
1.0
0.9
0.8
0.7
0.6
0
5
10
15
20
25
30