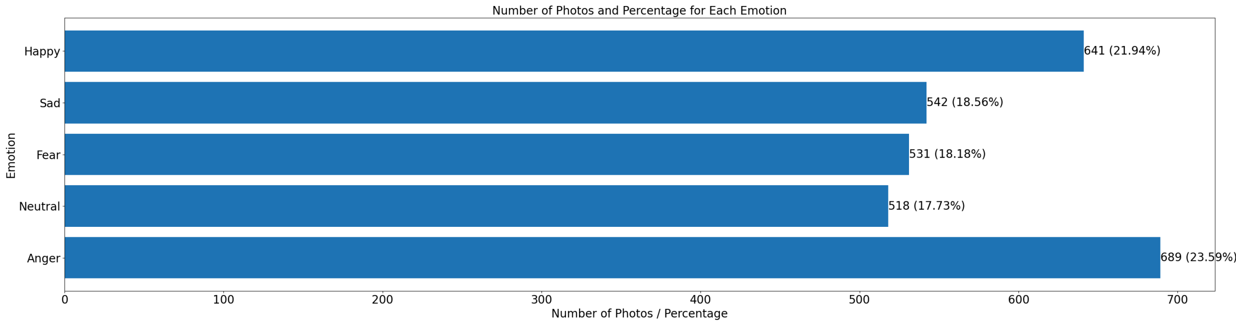
In [1]:
```
import warnings
warnings.filterwarnings('ignore')

import os
import matplotlib.pyplot as plt
import cv2
import random
import seaborn as sns
import numpy as np
import pandas as pd
import torch
# from torch.utils.data import PairTensor
import torchvision.models as models
import torch.nn as nn
import torch.optim as optim
from torchvision import transforms, datasets
import torchvision.transforms as transforms
from PIL import Image
from torch.optim.lr_scheduler import ReduceLROnPlateau
from torch.utils.data import Dataset, DataLoader
from sklearn.model_selection import train_test_split
import time
import copy
```

In [2]:
```
# Define paths to train and test data
data_path = '/Users/kritikasharma/Downloads/DATA_'
```

In [3]:
```
emotion_classes = ['Anger', 'Fear', 'Happy', 'Neutral', 'Sad']
```

In [4]:
```
# Initialize an empty dictionary to store counts for each emotion
emotion_counts = {}
total_photos = 0

# Traverse through each emotion folder
for emotion in os.listdir(data_path):
    if os.path.isdir(os.path.join(data_path, emotion)):
        # Count the number of photos in the emotion folder
        num_photos = len(os.listdir(os.path.join(data_path, emotion)))
        emotion_counts[emotion] = num_photos
        total_photos += num_photos

# Calculate percentage and format string for displaying counts and percentages
emotion_info = {emotion: {'count': count, 'percentage': (count / total_photos)

# Plotting the horizontal bar plot
plt.figure(figsize=(30, 8))
plt.barh(list(emotion_info.keys()), [info['count'] for info in emotion_info.va
plt.xlabel('Number of Photos / Percentage', fontsize=20)
plt.ylabel('Emotion',fontsize=20)
plt.title('Number of Photos and Percentage for Each Emotion', fontsize=20)
plt.gca().invert_yaxis()  # Invert y-axis to display emotions in descending or
plt.xticks(fontsize=20)
plt.yticks(fontsize=20)
plt.tight_layout()

# Display the counts and percentages on the bars
for i, (emotion, info) in enumerate(emotion_info.items()):
```

```
    count = info['count']
    percentage = info['percentage']
    plt.text(count, i, f'{count} ({percentage:.2f}%)', ha='left', va='center',

plt.show()
```



In [6]:

```
# Function to plot images
def plot_images(images, title):
    num_images = len(images)
    num_rows = len(emotion_classes)
    num_cols = 5  # Plot 5 images for each emotion
    plt.figure(figsize=(3 * num_cols, 3 * num_rows))
    for i, (emotion, img_paths) in enumerate(images.items()):
        for j, img_path in enumerate(img_paths[:5]):  # Plot only the first 5 i
            plt.subplot(num_rows, num_cols, i * num_cols + j + 1)
            img = cv2.imread(img_path)
            img = cv2.resize(img, (224, 224)) # Resize the image to a fixed siz
            img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)  # Convert the BGR image
            plt.imshow(img)
            plt.axis('off')
            if j == 0:
                plt.title(emotion)
    plt.suptitle(title, fontsize=20)
    plt.tight_layout()
    plt.show()

# Randomly select 5 images from each emotion class
random_images = {emotion: [] for emotion in emotion_classes}
for emotion_class in emotion_classes:
    emotion_path = os.path.join(data_path, emotion_class)
    image_files = os.listdir(emotion_path)
    random_images[emotion_class] = random.sample([os.path.join(emotion_path, in

# Plot the images
plot_images(random_images, "Randomly Selected Emotion Images")
```

In [7]:
```
# Initialize an empty list to store image file paths and their respective labe
data = []

# Append the image file paths with their respective labels to the data list
for emotion_class in emotion_classes:
    emotion_path = os.path.join(data_path, emotion_class)
    data.extend([(os.path.join(emotion_path, filename), emotion_class) for fil

# Convert the collected data into a DataFrame
df = pd.DataFrame(data, columns=['filepath', 'label'])

# Now let's see the first few rows of the dataframe
df.head()
```

Out[7]:

	filepath	label
0	/Users/kritikasharma/Downloads/DATA_/Anger/63.jpg	Anger
1	/Users/kritikasharma/Downloads/DATA_/Anger/7v.jpg	Anger
2	/Users/kritikasharma/Downloads/DATA_/Anger/ima...	Anger
3	/Users/kritikasharma/Downloads/DATA_/Anger/ima...	Anger
4	/Users/kritikasharma/Downloads/DATA_/Anger/ima...	Anger

In [8]:

```
# Convert labels to numeric
label_to_index = {label: index for index, label in enumerate(emotion_classes)}
df['label'] = df['label'].map(label_to_index)
df.head()
```

Out[8]:

	filepath	label
0	/Users/kritikasharma/Downloads/DATA_/Anger/63.jpg	0
1	/Users/kritikasharma/Downloads/DATA_/Anger/7v.jpg	0
2	/Users/kritikasharma/Downloads/DATA_/Anger/ima...	0
3	/Users/kritikasharma/Downloads/DATA_/Anger/ima...	0
4	/Users/kritikasharma/Downloads/DATA_/Anger/ima...	0

In [9]:

```
print("Total number of images in the dataset:", len(df))
```

```
Total number of images in the dataset: 2921
```

In [10]:

```
# Split the data into training and validation sets
train_df, val_df = train_test_split(df, test_size=0.2, random_state=42, strati
```

In [11]:

```
# Display the shape of the training and validation sets
print("Training data shape:", train_df.shape)
print("Validation data shape:", val_df.shape)
```

```
Training data shape: (2336, 2)
Validation data shape: (585, 2)
```

In [12]:

```
train_transforms = transforms.Compose([
    transforms.RandomResizedCrop(224),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(15),  # New: Randomly rotate images
    transforms.ColorJitter(brightness=0.1, contrast=0.1, saturation=0.1, hue=0
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
])

val_transforms = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
])
```

In [13]:

```
# Define a custom dataset
class MoodDataset(Dataset):
```

```
    def __init__(self, dataframe, transform=None):
        self.dataframe = dataframe
        self.transform = transform

    def __len__(self):
        return len(self.dataframe)

    def __getitem__(self, idx):
        img_path, label = self.dataframe.iloc[idx]
        image = Image.open(img_path).convert('RGB')  # Ensure image is in RGB
        if self.transform:
            image = self.transform(image)
        return image, label
```

In [14]:

```
# Create training and validation datasets
train_dataset = MoodDataset(train_df, transform=train_transforms)
val_dataset = MoodDataset(val_df, transform=val_transforms)

# Create the DataLoader for training data
train_loader = DataLoader(train_dataset, batch_size=10, shuffle=True, num_work

# Create the DataLoader for validation data
val_loader = DataLoader(val_dataset, batch_size=10, shuffle=False, num_workers

# Now you can define the dataloaders dictionary
dataloaders = {'train': train_loader, 'val': val_loader}

# Create dataloaders
batch_size = 10
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=batch_size)
```

In [15]:

```
# Load a pre-trained ResNet
model = models.resnet50(pretrained=True)

# Modify the classifier
num_ftrs = model.fc.in_features
model.fc = nn.Linear(num_ftrs, len(emotion_classes))

# Move the model to the GPU if available
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
model = model.to(device)
```

In [16]:

```
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.0001)
scheduler = ReduceLROnPlateau(optimizer, 'min', patience=5)
```

In [17]:

```
def train_model(model, dataloaders, criterion, optimizer, num_epochs, schedule
    since = time.time()

    train_loss_history = []
    train_acc_history = []
    val_loss_history = []
    val_acc_history = []

    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0
```

```
    for epoch in range(num_epochs):
        print('Epoch {}/{}'.format(epoch + 1, num_epochs))
        print('-' * 10)

        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()
            else:
                model.eval()

            running_loss = 0.0
            running_corrects = 0

            for inputs, labels in dataloaders[phase]:
                inputs = inputs.to(device)
                labels = labels.to(device)

                optimizer.zero_grad()

                #forward
                with torch.set_grad_enabled(phase == 'train'):
                    outputs = model(inputs)
                    _, preds = torch.max(outputs, 1)
                    loss = criterion(outputs, labels)

                    #backward + optimize only of in training phase
                    if phase == 'train':
                        loss.backward()
                        optimizer.step()

                #statistics
                running_loss += loss.item() * inputs.size(0)
                running_corrects += torch.sum(preds == labels.data)

            epoch_loss = running_loss / len(dataloaders[phase].dataset)
            epoch_acc = running_corrects.double() / len(dataloaders[phase].data

            print('{} Loss: {:.4f} Acc: {:.4f}'.format(phase, epoch_loss, epoch

            if phase == 'train':
                train_loss_history.append(epoch_loss)
                train_acc_history.append(epoch_acc)
            else:
                val_loss_history.append(epoch_loss)
                val_acc_history.append(epoch_acc)

            # deep copy the model
            if phase == 'val' and epoch_acc > best_acc:
                best_acc = epoch_acc
                best_model_wts = copy.deepcopy(model.state_dict())

            # step the scheduler on each epoch end if its not ReduceLROnPlateau
            if phase == 'train' and scheduler and not isinstance(scheduler, Re
                scheduler.step()
            # For ReduceLROnPlateau, step with the validation loss
            elif phase == 'val' and scheduler and isinstance(scheduler, Reduce
                scheduler.step(epoch_loss)

        print()
```

```
    time_elapsed = time.time() - since
    print('Training complete in {:.0f}m {:.0f}s'.format(time_elapsed // 60, ti
    print('Best val Acc: {:4f}'.format(best_acc))

    model.load_state_dict(best_model_wts)

    history = {
        'train_loss': train_loss_history,
        'train_acc': train_acc_history,
        'val_loss': val_loss_history,
        'val_acc': val_acc_history
    }

    return model, history
```

In [19]:
```
# Set up dataloaders as a dictionary
dataloaders = {'train': train_loader, 'val': val_loader}

# Train the model
trained_model, history = train_model(model, dataloaders, criterion, optimizer,
```

```
Epoch 1/50
----------
train Loss: 1.3495 Acc: 0.4255
val Loss: 1.0989 Acc: 0.5709

Epoch 2/50
----------
train Loss: 1.1164 Acc: 0.5655
val Loss: 0.7977 Acc: 0.6718

Epoch 3/50
----------
train Loss: 0.9997 Acc: 0.6036
val Loss: 0.7643 Acc: 0.6889

Epoch 4/50
----------
train Loss: 0.9144 Acc: 0.6438
val Loss: 0.6564 Acc: 0.7521

Epoch 5/50
----------
train Loss: 0.8727 Acc: 0.6601
val Loss: 0.7231 Acc: 0.7299

Epoch 6/50
----------
train Loss: 0.8584 Acc: 0.6734
val Loss: 0.6562 Acc: 0.7487

Epoch 7/50
----------
train Loss: 0.8140 Acc: 0.6777
val Loss: 0.6651 Acc: 0.7778

Epoch 8/50
----------
train Loss: 0.7799 Acc: 0.7080
val Loss: 0.6462 Acc: 0.7624

Epoch 9/50
----------
train Loss: 0.7428 Acc: 0.7183
val Loss: 0.6673 Acc: 0.7624

Epoch 10/50
----------
train Loss: 0.7317 Acc: 0.7299
val Loss: 0.5944 Acc: 0.7692

Epoch 11/50
----------
train Loss: 0.7204 Acc: 0.7299
val Loss: 0.5713 Acc: 0.8017

Epoch 12/50
----------
train Loss: 0.6856 Acc: 0.7393
val Loss: 0.7440 Acc: 0.7538
```

```
Epoch 13/50
----------
train Loss: 0.6900 Acc: 0.7509
val Loss: 0.6102 Acc: 0.7846

Epoch 14/50
----------
train Loss: 0.6842 Acc: 0.7457
val Loss: 0.6177 Acc: 0.7812

Epoch 15/50
----------
train Loss: 0.6651 Acc: 0.7526
val Loss: 0.5298 Acc: 0.8068

Epoch 16/50
----------
train Loss: 0.6303 Acc: 0.7727
val Loss: 0.6343 Acc: 0.7692

Epoch 17/50
----------
train Loss: 0.6342 Acc: 0.7551
val Loss: 0.6686 Acc: 0.7556

Epoch 18/50
----------
train Loss: 0.6474 Acc: 0.7440
val Loss: 0.5858 Acc: 0.8085

Epoch 19/50
----------
train Loss: 0.5784 Acc: 0.7821
val Loss: 0.5577 Acc: 0.8068

Epoch 20/50
----------
train Loss: 0.5943 Acc: 0.7825
val Loss: 0.6345 Acc: 0.7983

Epoch 21/50
----------
train Loss: 0.5942 Acc: 0.7757
val Loss: 0.6457 Acc: 0.7658

Epoch 22/50
----------
train Loss: 0.4968 Acc: 0.8202
val Loss: 0.5101 Acc: 0.8274

Epoch 23/50
----------
train Loss: 0.4552 Acc: 0.8283
val Loss: 0.5043 Acc: 0.8188

Epoch 24/50
----------
train Loss: 0.4321 Acc: 0.8433
val Loss: 0.5073 Acc: 0.8325
```

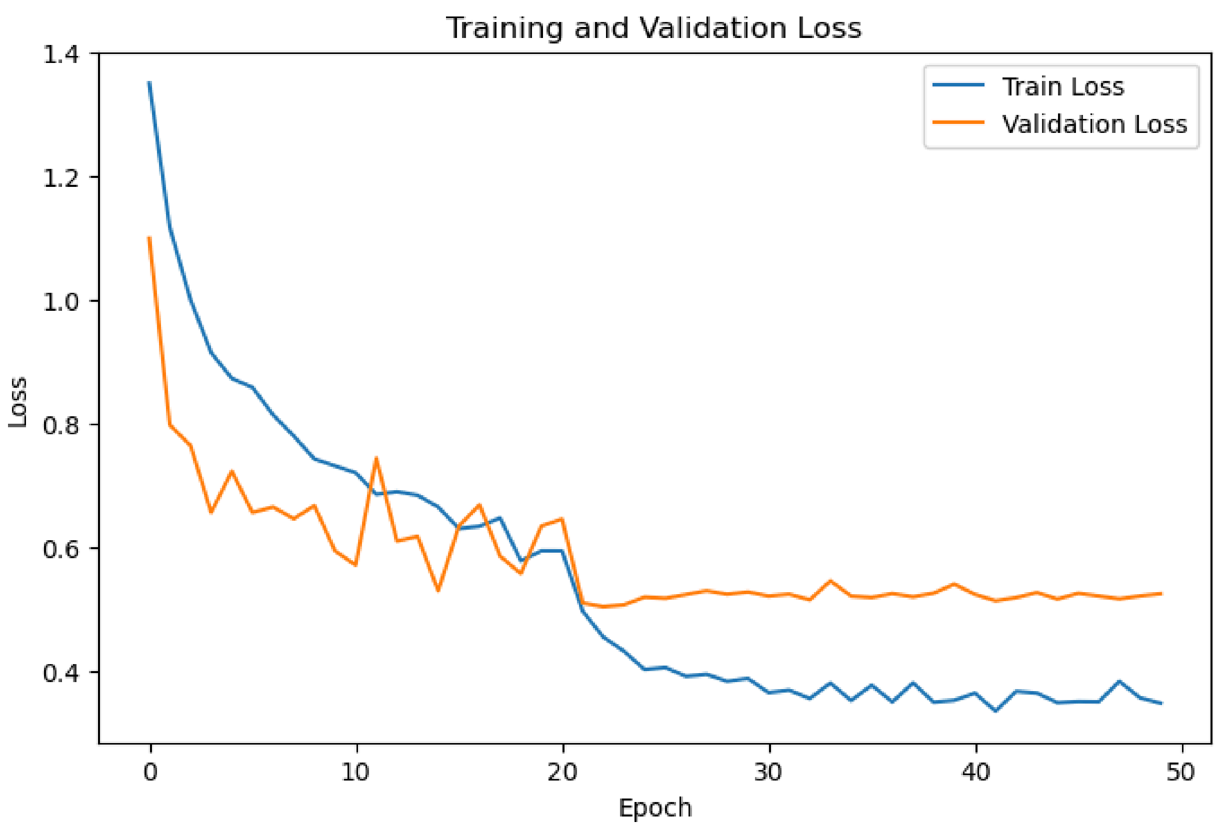
```
Epoch 25/50
----------
train Loss: 0.4027 Acc: 0.8489
val Loss: 0.5197 Acc: 0.8222

Epoch 26/50
----------
train Loss: 0.4060 Acc: 0.8459
val Loss: 0.5178 Acc: 0.8291

Epoch 27/50
----------
train Loss: 0.3919 Acc: 0.8536
val Loss: 0.5238 Acc: 0.8325

Epoch 28/50
----------
train Loss: 0.3951 Acc: 0.8493
val Loss: 0.5300 Acc: 0.8308

Epoch 29/50
----------
train Loss: 0.3838 Acc: 0.8592
val Loss: 0.5242 Acc: 0.8359

Epoch 30/50
----------
train Loss: 0.3885 Acc: 0.8579
val Loss: 0.5280 Acc: 0.8325

Epoch 31/50
----------
train Loss: 0.3654 Acc: 0.8686
val Loss: 0.5213 Acc: 0.8376

Epoch 32/50
----------
train Loss: 0.3693 Acc: 0.8652
val Loss: 0.5244 Acc: 0.8393

Epoch 33/50
----------
train Loss: 0.3559 Acc: 0.8579
val Loss: 0.5153 Acc: 0.8376

Epoch 34/50
----------
train Loss: 0.3809 Acc: 0.8622
val Loss: 0.5458 Acc: 0.8308

Epoch 35/50
----------
train Loss: 0.3526 Acc: 0.8720
val Loss: 0.5214 Acc: 0.8376

Epoch 36/50
----------
train Loss: 0.3774 Acc: 0.8626
val Loss: 0.5191 Acc: 0.8376
```

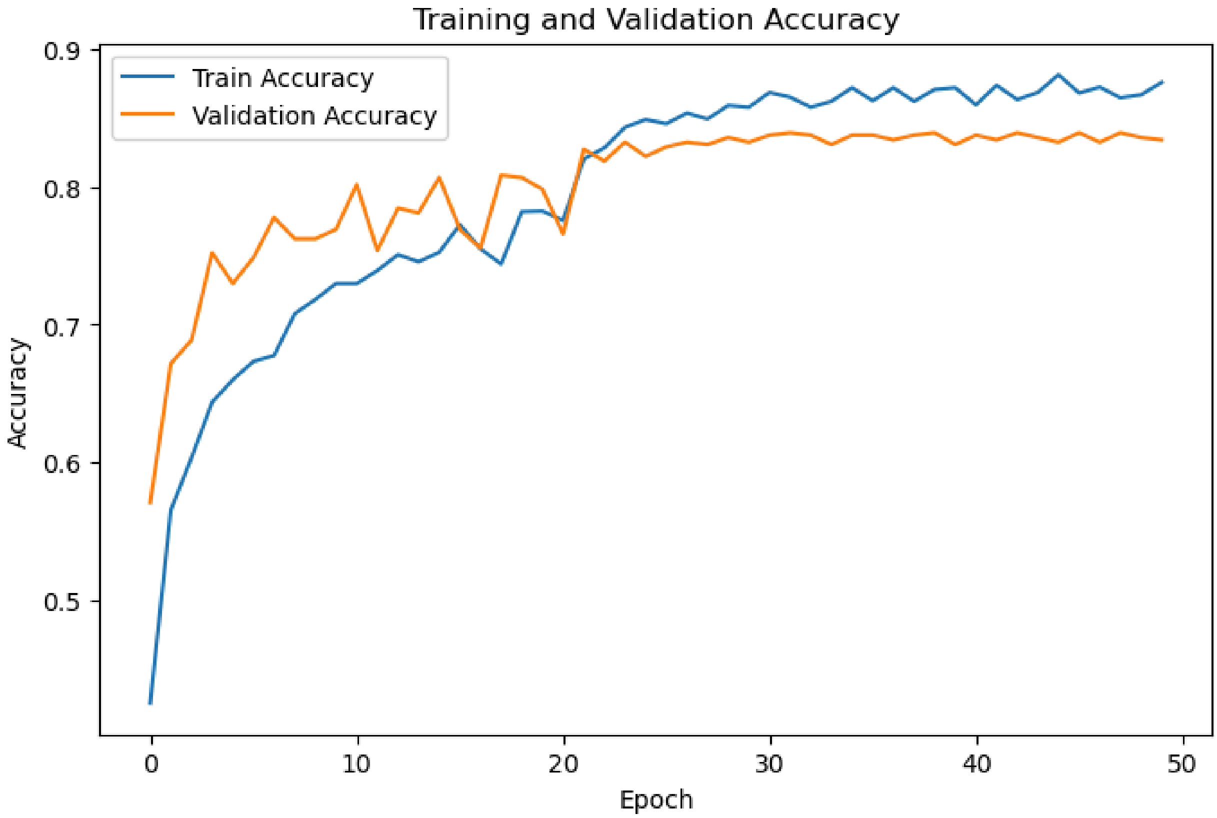
```
Epoch 37/50
----------
train Loss: 0.3503 Acc: 0.8720
val Loss: 0.5253 Acc: 0.8342

Epoch 38/50
----------
train Loss: 0.3812 Acc: 0.8622
val Loss: 0.5202 Acc: 0.8376

Epoch 39/50
----------
train Loss: 0.3500 Acc: 0.8707
val Loss: 0.5259 Acc: 0.8393

Epoch 40/50
----------
train Loss: 0.3530 Acc: 0.8720
val Loss: 0.5407 Acc: 0.8308

Epoch 41/50
----------
train Loss: 0.3646 Acc: 0.8596
val Loss: 0.5241 Acc: 0.8376

Epoch 42/50
----------
train Loss: 0.3357 Acc: 0.8737
val Loss: 0.5138 Acc: 0.8342

Epoch 43/50
----------
train Loss: 0.3675 Acc: 0.8634
val Loss: 0.5189 Acc: 0.8393

Epoch 44/50
----------
train Loss: 0.3647 Acc: 0.8686
val Loss: 0.5269 Acc: 0.8359

Epoch 45/50
----------
train Loss: 0.3492 Acc: 0.8814
val Loss: 0.5166 Acc: 0.8325

Epoch 46/50
----------
train Loss: 0.3511 Acc: 0.8682
val Loss: 0.5257 Acc: 0.8393

Epoch 47/50
----------
train Loss: 0.3507 Acc: 0.8724
val Loss: 0.5214 Acc: 0.8325

Epoch 48/50
----------
train Loss: 0.3837 Acc: 0.8647
val Loss: 0.5168 Acc: 0.8393
```

```
Epoch 49/50
----------
train Loss: 0.3569 Acc: 0.8669
val Loss: 0.5215 Acc: 0.8359

Epoch 50/50
----------
train Loss: 0.3483 Acc: 0.8759
val Loss: 0.5250 Acc: 0.8342

Training complete in 1019m 11s
Best val Acc: 0.839316
```

In [23]:

```
plt.figure(figsize=(8, 5))
plt.plot(history['train_loss'], label='Train Loss')
plt.plot(history['val_loss'], label='Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()
plt.show()

plt.figure(figsize=(8, 5))
plt.plot(history['train_acc'], label='Train Accuracy')
plt.plot(history['val_acc'], label='Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracy')
plt.legend()
plt.show()
```





In [24]:
```
torch.save(trained_model.state_dict(), 'mood_recognition_model1.pth')
```

In [25]:
```
images = ['/Users/kritikasharma/Downloads/happy.jpeg',
          '/Users/kritikasharma/Downloads/Angry.jpeg',
          '/Users/kritikasharma/Downloads/sad.jpeg',
          '/Users/kritikasharma/Downloads/neautral.jpeg',
          '/Users/kritikasharma/Downloads/fear.jpeg']
```

In [26]:
```
# Load the trained model
# model = models.resnet50(pretrained=False)
model.fc = nn.Linear(model.fc.in_features, len(emotion_classes))
model.load_state_dict(torch.load('/Users/kritikasharma/Downloads/mood_recognit
model.eval()
model.to(device)
```

Out[26]:
```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bi
as=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_s
tats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mo
de=False)
  (layer1): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runni
ng_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runni
ng_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runni
ng_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runni
ng_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runni
ng_stats=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_runni
ng_stats=True)
      (conv3): Conv2d(64, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer2): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1,
```

```
1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (relu): ReLU(inplace=True)
    )
    (3): Bottleneck(
      (conv1): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv3): Conv2d(128, 512, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn3): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer3): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(512, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
```

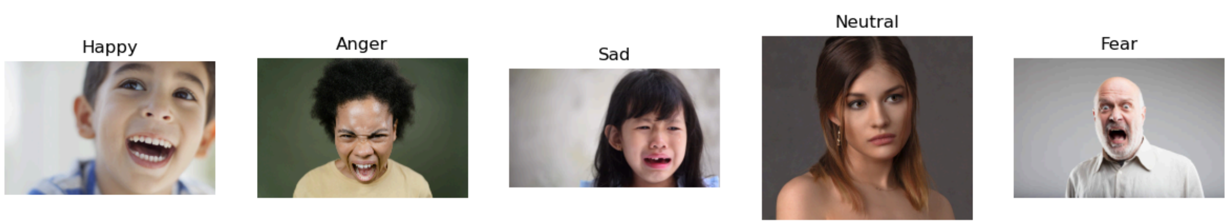
```
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(512, 1024, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=True)
    )
    (3): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=True)
    )
    (4): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=Fals
```

```
e)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=True)
    )
    (5): Bottleneck(
      (conv1): Conv2d(1024, 256, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv3): Conv2d(256, 1024, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn3): BatchNorm2d(1024, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (layer4): Sequential(
    (0): Bottleneck(
      (conv1): Conv2d(1024, 512, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=True)
      (downsample): Sequential(
        (0): Conv2d(1024, 2048, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      )
    )
    (1): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=Fals
```

```
e)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=True)
    )
    (2): Bottleneck(
      (conv1): Conv2d(2048, 512, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_runn
ing_stats=True)
      (conv3): Conv2d(512, 2048, kernel_size=(1, 1), stride=(1, 1), bias=Fals
e)
      (bn3): BatchNorm2d(2048, eps=1e-05, momentum=0.1, affine=True, track_run
ning_stats=True)
      (relu): ReLU(inplace=True)
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Linear(in_features=2048, out_features=5, bias=True)
)
```

In [34]:

```python
# Load and preprocess the input image
plt.figure(figsize=(15, 5))
for i, image_path in enumerate(images):
    input_image = Image.open(image_path)
    input_tensor = val_transforms(input_image).unsqueeze(0)  # Adding a batch 

    # Perform inference
    with torch.no_grad():
        model.eval()  # Set the model to evaluation mode
        output = model(input_tensor)

    # Interpret the model's output to determine the predicted emotion
    predicted_emotion_index = torch.argmax(output, dim=1).item()
    # Map the index to the corresponding emotion label
    predicted_emotion = emotion_classes[predicted_emotion_index]

    #print("Predicted emotion:", predicted_emotion)
    # Plot the image
    plt.subplot(1, len(images), i+1)
    plt.imshow(input_image)
    plt.axis('off')

    # Write the predicted emotion on top of the image
    plt.title(predicted_emotion)

plt.show()
```



In [28]:
```
# Load face cascade classifier
face_cascade = cv2.CascadeClassifier(cv2.data.haarcascades + 'haarcascade_fron

# Start capturing video
cap = cv2.VideoCapture(0)
```

In [29]:
```
while True:
    # Capture frame-by-frame
    ret, frame = cap.read()

    # Check if the frame is empty
    if not ret:
        print("Error: Failed to capture frame")
        break

    # Convert frame to grayscale
    gray_frame = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)

    # Detect faces in the frame
    faces = face_cascade.detectMultiScale(gray_frame, scaleFactor=1.1, minNeigl

    for (x, y, w, h) in faces:
        # Extract the face ROI (Region of Interest)
        face_roi = gray_frame[y:y + h, x:x + w]

        # Preprocess the face ROI
        pil_image = Image.fromarray(face_roi)

        # Convert grayscale image to RGB
        pil_image_rgb = pil_image.convert('RGB')

        # Apply transformations
        input_tensor = val_transforms(pil_image_rgb).unsqueeze(0)

        # Perform inference using the model
        with torch.no_grad():
            model.eval()
            output = model(input_tensor)
            _, predicted = torch.max(output, 1)
            emotion = emotion_classes[predicted.item()]

        # Draw rectangle around face and label with predicted emotion
        cv2.rectangle(frame, (x, y), (x + w, y + h), (0, 0, 255), 2)
        cv2.putText(frame, emotion, (x, y - 10), cv2.FONT_HERSHEY_SIMPLEX, 0.9

    # Display the resulting frame
    cv2.imshow('Real-time Emotion Detection', frame)

    # Press 'q' to exit
    if cv2.waitKey(1) & 0xFF == ord('q'):
        break
```

In [30]:
```
# Release webcam and close windows
cap.release()
cv2.destroyAllWindows()
```

In [ ]:
```
```