Section 7: Fulfilling Requirements 6, 7

Please note, requirement 6 is implemented in FinalNotebook2_1.ipynb and this is a continuation of this section

Requirement 7: For the modified method(s), repeat the analysis in 4) but only pertaining to the items you choose to improve on as justified in 6). [10%]

Repeating feature and classifier analysis on the proposed modifications model

```
In [ ]: # mounting the drive
        from google.colab import drive
        drive.mount('/content/drive', force_remount=True)
       Mounted at /content/drive
In [ ]: # all modules/libraries needed to run this notebook
        from collections import defaultdict
        from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, confusion_matrix
        from sklearn.metrics.pairwise import cosine_similarity
        from torchvision.datasets import ImageFolder
        from torchvision.models import googlenet
        import torchvision.transforms as transforms
        from torch.utils.data import DataLoader
        import matplotlib.pyplot as plt
        import seaborn as sns
        import torch.nn as nn
        import numpy as np
        import torch
        from torchvision import datasets, transforms
        from tqdm import tqdm
        import torchvision.models as models
        import torch.optim as optim
        from torch.utils.data import ConcatDataset
        import random
        import pandas as pd
        os.environ["CUBLAS_WORKSPACE_CONFIG"] = ":4096:8"
        from PIL import Image
```

Classifier Analysis

Experimental Setup

The analysis will focus on validation dataset in Batch-1 (seedsegment/test), and uses Accuracy, Precision, Recall, F1 Score and AUC Score to assess how consistent the proposed modification model's classification performance.

• Transformations Applied:

```
    Translation: Shift image by ±10%, ±20%, ±30%
    Rotation: Rotate by ±15°, ±30°, ±45°, ±90°, ±180°, ±360°
    Scaling: Resize image by 0.8×, 1.2×, 1.5×
    Noise: σ = 0.01, 0.05, 0.1
```

5. *Illumination*: brightness change to 0.5 (dimmer than normal), 1.5 (brighter than normal)

Each transformation is applied individually to measure its isolated effect. GoogleNet retrained on the augmented_seed_segment_train_googlenet dataset (from Requirment 6) will be used to compare the **original data's vs. transformed data's classification**.

Outcome This analysis will provide empirical insight into the classification robustness of proposed modification GoogleNet when subjected to image transformations.

The following cells loads the validation dataset, feeds it into the modified fine-tuned GoogleNet model. Then, the metrics mentioned above and relevent confusion matrices are outputted.

```
In []: device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    model = googlenet(weights=None, aux_logits=False, num_classes=2)
    model.fc = nn.Linear(1024, 2)
    model.load_state_dict(torch.load("/content/drive/MyDrive/Computer Vision Coursework/models/googlenet_trained_with_aug_modifications_batch1.pth"), strict=False)
    model.to(device)
```

/usr/local/lib/python3.11/dist-packages/torchvision/models/googlenet.py:47: FutureWarning: The default weight initialization of GoogleNet will be changed in future e releases of torchvision. If you wish to keep the old behavior (which leads to long initialization times due to scipy/scipy#11299), please set init_weights=True. warnings.warn(

```
Out[]: GoogLeNet(
          (conv1): BasicConv2d(
             (conv): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
             (bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
          (maxpool1): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=True)
           (conv2): BasicConv2d(
             (conv): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
             (bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
           (conv3): BasicConv2d(
             (conv): Conv2d(64, 192, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
             (bn): BatchNorm2d(192, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
           (maxpool2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=True)
          (inception3a): Inception(
             (branch1): BasicConv2d(
               (conv): Conv2d(192, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
               (bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
             (branch2): Sequential(
               (0): BasicConv2d(
                 (conv): Conv2d(192, 96, kernel_size=(1, 1), stride=(1, 1), bias=False)
                 (bn): BatchNorm2d(96, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
               (1): BasicConv2d(
                 (conv): Conv2d(96, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
                 (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
               )
             (branch3): Sequential(
               (0): BasicConv2d(
                 (conv): Conv2d(192, 16, kernel_size=(1, 1), stride=(1, 1), bias=False)
                 (bn): BatchNorm2d(16, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
               (1): BasicConv2d(
                 (conv): Conv2d(16, 32, kernel size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
                 (bn): BatchNorm2d(32, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
               )
             (branch4): Sequential(
               (0): MaxPool2d(kernel_size=3, stride=1, padding=1, dilation=1, ceil_mode=True)
               (1): BasicConv2d(
                 (conv): Conv2d(192, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
                 (bn): BatchNorm2d(32, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
            )
           (inception3b): Inception(
             (branch1): BasicConv2d(
               (conv): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
               (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
             (branch2): Sequential(
               (0): BasicConv2d(
                 (conv): Conv2d(256, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
                 (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
               (1): BasicConv2d(
                 (conv): Conv2d(128, 192, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
                 (bn): BatchNorm2d(192, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
               )
             (branch3): Sequential(
               (0): BasicConv2d(
                 (conv): Conv2d(256, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
                 (bn): BatchNorm2d(32, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
               (1): BasicConv2d(
                 (conv): Conv2d(32, 96, kernel\_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
                 (bn): BatchNorm2d(96, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
             (branch4): Sequential(
               (0): MaxPool2d(kernel_size=3, stride=1, padding=1, dilation=1, ceil_mode=True)
                 (conv): Conv2d(256, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
                 (bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
               )
           (maxpool3): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=True)
           (inception4a): Inception(
             (branch1): BasicConv2d(
               (conv): Conv2d(480, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
               (bn): BatchNorm2d(192, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
             (branch2): Sequential(
               (0): BasicConv2d(
                 (conv): Conv2d(480, 96, kernel\_size=(1, 1), stride=(1, 1), bias=False)
                 (bn): BatchNorm2d(96, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
               (1): BasicConv2d(
                 (conv): Conv2d(96, 208, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
                 (bn): BatchNorm2d(208, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
               )
             (branch3): Sequential(
               (0): BasicConv2d(
                 (conv): Conv2d(480, 16, kernel_size=(1, 1), stride=(1, 1), bias=False)
                 (bn): BatchNorm2d(16, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
               (1): BasicConv2d(
                 (conv): Conv2d(16, 48, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
                 (bn): BatchNorm2d(48, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
```

```
)
  (branch4): Sequential(
    (0): MaxPool2d(kernel_size=3, stride=1, padding=1, dilation=1, ceil_mode=True)
    (1): BasicConv2d(
      (conv): Conv2d(480, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
(inception4b): Inception(
 (branch1): BasicConv2d(
    (conv): Conv2d(512, 160, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(160, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
 (branch2): Sequential(
    (0): BasicConv2d(
      (conv): Conv2d(512, 112, kernel_size=(1, 1), stride=(1, 1), bias=False)
     (bn): BatchNorm2d(112, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    (1): BasicConv2d(
      (conv): Conv2d(112, 224, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn): BatchNorm2d(224, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
  (branch3): Sequential(
    (0): BasicConv2d(
     (conv): Conv2d(512, 24, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(24, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    (1): BasicConv2d(
      (conv): Conv2d(24, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
  (branch4): Sequential(
    (0): MaxPool2d(kernel_size=3, stride=1, padding=1, dilation=1, ceil_mode=True)
    (1): BasicConv2d(
      (conv): Conv2d(512, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
 )
(inception4c): Inception(
 (branch1): BasicConv2d(
    (conv): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
 (branch2): Sequential(
    (0): BasicConv2d(
     (conv): Conv2d(512, 128, kernel size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    (1): BasicConv2d(
     (conv): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn): BatchNorm2d(256, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
   )
  (branch3): Sequential(
      (conv): Conv2d(512, 24, kernel_size=(1, 1), stride=(1, 1), bias=False)
     (bn): BatchNorm2d(24, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    (1): BasicConv2d(
      (conv): Conv2d(24, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    )
 (branch4): Sequential(
    (0): MaxPool2d(kernel_size=3, stride=1, padding=1, dilation=1, ceil_mode=True)
    (1): BasicConv2d(
      (conv): Conv2d(512, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
(inception4d): Inception(
 (branch1): BasicConv2d(
    (conv): Conv2d(512, 112, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(112, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
  (branch2): Sequential(
    (0): BasicConv2d(
     (conv): Conv2d(512, 144, kernel_size=(1, 1), stride=(1, 1), bias=False)
     (bn): BatchNorm2d(144, eps=0.001, momentum=0.1, affine=True, track running stats=True)
      (conv): \ Conv2d(144,\ 288,\ kernel\_size=(3,\ 3),\ stride=(1,\ 1),\ padding=(1,\ 1),\ bias=False)
      (bn): BatchNorm2d(288, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    )
  (branch3): Sequential(
    (0): BasicConv2d(
     (conv): Conv2d(512, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(32, eps=0.001, momentum=0.1, affine=True, track_running stats=True)
    (1): BasicConv2d(
     (conv): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    )
  (branch4): Sequential(
    (0): MaxPool2d(kernel_size=3, stride=1, padding=1, dilation=1, ceil_mode=True)
    (1): BasicConv2d(
     (conv): Conv2d(512, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
```

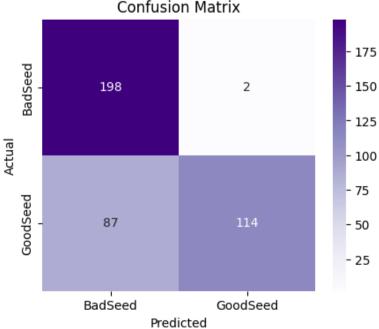
```
)
(inception4e): Inception(
  (branch1): BasicConv2d(
    (conv): Conv2d(528, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(256, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
  (branch2): Sequential(
    (0): BasicConv2d(
      (conv): Conv2d(528, 160, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(160, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    (1): BasicConv2d(
      (conv): Conv2d(160, 320, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn): BatchNorm2d(320, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
  (branch3): Sequential(
    (0): BasicConv2d(
      (conv): Conv2d(528, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(32, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    (1): BasicConv2d(
      (conv): Conv2d(32, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    )
  (branch4): Sequential(
    (0): MaxPool2d(kernel_size=3, stride=1, padding=1, dilation=1, ceil_mode=True)
    (1): BasicConv2d(
      (conv): Conv2d(528, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
 )
(maxpool4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=True)
(inception5a): Inception(
  (branch1): BasicConv2d(
    (conv): Conv2d(832, 256, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(256, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
  (branch2): Sequential(
    (0): BasicConv2d(
      (conv): Conv2d(832, 160, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(160, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    (1): BasicConv2d(
      (conv): Conv2d(160, 320, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn): BatchNorm2d(320, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
  (branch3): Sequential(
    (0): BasicConv2d(
      (conv): Conv2d(832, 32, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(32, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    (1): BasicConv2d(
      (conv): Conv2d(32, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    )
  (branch4): Sequential(
    (0): MaxPool2d(kernel_size=3, stride=1, padding=1, dilation=1, ceil_mode=True)
    (1): BasicConv2d(
      (conv): Conv2d(832, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
(inception5b): Inception(
  (branch1): BasicConv2d(
    (conv): Conv2d(832, 384, kernel_size=(1, 1), stride=(1, 1), bias=False)
    (bn): BatchNorm2d(384, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
  (branch2): Sequential(
      (conv): Conv2d(832, 192, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(192, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    (1): BasicConv2d(
      (conv): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn): BatchNorm2d(384, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    )
  (branch3): Sequential(
    (0): BasicConv2d(
      (conv): Conv2d(832, 48, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(48, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    (1): BasicConv2d(
      (conv): Conv2d(48, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    )
  (branch4): Sequential(
    (0): MaxPool2d(kernel_size=3, stride=1, padding=1, dilation=1, ceil mode=True)
    (1): BasicConv2d(
      (conv): Conv2d(832, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
      (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    )
 )
(avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
(dropout): Dropout(p=0.2, inplace=False)
```

```
In [ ]: # function to evaluate the model on the test set (batch 2 and 3)
        import torch
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, confusion_matrix
        def evaluate_model(model, dataloader, test_dataset):
            model.eval()
            all_preds = []
            all_labels = []
            all_probs = [] # auc
            with torch.no_grad():
                 for inputs, labels in dataloader:
                    inputs, labels = inputs.to(device), labels.to(device)
                    outputs = model(inputs)
                    if isinstance(outputs, tuple): # googlenet might return aux output
                         outputs = outputs[0]
                    # predicted class labels
                     _, preds = torch.max(outputs, 1)
                    all_preds.extend(preds.cpu().numpy())
                    all_labels.extend(labels.cpu().numpy())
                    # get predicted probabilities for AUC (softmax output)
                    probs = torch.nn.functional.softmax(outputs, dim=1) # get probabilities
                    all_probs.extend(probs.cpu().numpy()[:, 1]) # for binary classification, class 1 probabilities
            all_preds = np.array(all_preds)
            all_labels = np.array(all_labels)
            all_probs = np.array(all_probs)
            acc = accuracy_score(all_labels, all_preds)
            prec = precision_score(all_labels, all_preds, average='binary')
            rec = recall_score(all_labels, all_preds, average='binary')
            f1 = f1_score(all_labels, all_preds, average='binary')
            auc = roc_auc_score(all_labels, all_probs) # AUC score
            cm = confusion_matrix(all_labels, all_preds)
            print(f"Accuracy: {acc:.3f}")
            print(f"Precision: {prec:.3f}")
            print(f"Recall: {rec:.3f}")
            print(f"F1 Score: {f1:.3f}")
            print(f"AUC Score: {auc:.3f}")
            # Plot confusion matrix
            plt.figure(figsize=(5, 4))
            sns.heatmap(cm, annot=True, fmt='d', cmap='Purples',
                         xticklabels=test_dataset.classes,
                         yticklabels=test_dataset.classes)
            plt.xlabel("Predicted")
            plt.ylabel("Actual")
            plt.title("Confusion Matrix")
            plt.show()
            return acc, prec, rec, f1, auc
In [ ]: def add_gaussian_noise(img, mean, std):
            noise = torch.randn_like(img) * std + mean
            noisy_img = img + noise
            return torch.clamp(noisy_img, 0, 1) # pixel values remain valid
        def add_random_translation(img, max_shift):
            translation = transforms.RandomAffine(degrees=0, translate=(max shift, max shift))
            return translation(img)
        def add_random_rotation(img, max_angle):
            rotation = transforms.RandomRotation(degrees=max_angle)
            return rotation(img)
        def add_random_scaling(img, scale_val):
            scaling = transforms.RandomAffine(degrees=0, scale=(scale_val, scale_val))
            return scaling(img)
        def add_random_illumination(img, brightness):
            illumination = transforms.ColorJitter(brightness=brightness)
            return illumination(img)
        # creating the different transforms to apply to the train set before training the feature extractor for googlenet
        resize_shape = (299, 299)
        mean = [0.5035, 0.5035, 0.4966]
        std = [0.2686, 0.2735, 0.2766]
        def create_transform(augmentation_func=None, **kwargs):
            \texttt{aug} = \texttt{transforms.Lambda}(\textbf{lambda} \ \texttt{x: augmentation\_func}(\texttt{x, **kwargs})) \ \textbf{if augmentation\_func else lambda} \ \texttt{x: x}
            return transforms.Compose([
                transforms.Resize(resize_shape),
                transforms.ToTensor(),
                aug,
                 transforms.Normalize(mean=mean, std=std)
            ])
        original_transform = create_transform(None)
        # brightness 0.5 & 1.5
        transform_brightness0_5 = create_transform(add_random_illumination, brightness=0.5)
        transform_brightness1_5 = create_transform(add_random_illumination, brightness=1.5)
        # noise 0.01, 0.05, 0.1
```

(fc): Linear(in_features=1024, out_features=2, bias=True)

```
# scale 0.8, 1.2, 1.5
        transform_scale0_8 = create_transform(add_random_scaling, scale_val=0.8)
        transform_scale1_2 = create_transform(add_random_scaling, scale_val=1.2)
        transform_scale1_5 = create_transform(add_random_scaling, scale_val=1.5)
        # rotate 15,30,45,90,180,360
        transform_rotate15 = create_transform(add_random_rotation, max_angle=15)
        transform_rotate30 = create_transform(add_random_rotation, max_angle=30)
        transform_rotate45 = create_transform(add_random_rotation, max_angle=45)
        transform_rotate90 = create_transform(add_random_rotation, max_angle=90)
        transform_rotate180 = create_transform(add_random_rotation, max_angle=180)
        transform_rotate360 = create_transform(add_random_rotation, max_angle=360)
        # translate 0.1, 0.2, 0.3
        transform_translate0_1 = create_transform(add_random_translation, max_shift=0.1)
        transform_translate0_2 = create_transform(add_random_translation, max_shift=0.2)
        transform_translate0_3 = create_transform(add_random_translation, max_shift=0.3)
In [ ]: val_dir = "/content/drive/MyDrive/Computer Vision Coursework/seedsegment/test"
        # Define the transformations and corresponding labels
        transformations = [
            (transform_brightness0_5, "Brightness=0.5"),
            (transform_brightness1_5, "Brightness=1.5"),
            (transform_noise0_01, "Noise=0.01"),
            (transform_noise0_05, "Noise=0.05"),
            (transform_noise0_1, "Noise=0.1"),
            (transform_scale0_8, "Scale=0.8"),
            (transform_scale1_2, "Scale=1.2"),
            (transform_scale1_5, "Scale=1.5"),
            (transform_rotate15, "Rotate=15"),
            (transform_rotate30, "Rotate=30"),
            (transform_rotate45, "Rotate=45"),
            (transform_rotate90, "Rotate=90"),
            (transform_rotate180, "Rotate=180"),
            (transform_rotate360, "Rotate=360"),
            (transform_translate0_1, "Translate=0.1"),
            (transform_translate0_2, "Translate=0.2"),
            (transform_translate0_3, "Translate=0.3")
        metrics_dict = {
            "Metric": ["Accuracy", "Precision", "Recall", "F1 Score", "AUC"],
        for transform, label in transformations:
            val_dataset = ImageFolder(root=val_dir, transform=transform)
            val_loader = DataLoader(val_dataset, batch_size=32, shuffle=False, num_workers=2)
            print(f"Evaluating on validation set ({label}):")
            acc, prec, rec, f1, auc = evaluate_model(model, val_loader, val_dataset)
            metrics_dict[label] = [acc, prec, rec, f1, auc]
        metrics_df = pd.DataFrame(metrics_dict)
        metrics_df.to_csv("/content/drive/MyDrive/Computer Vision Coursework/results/evaluation_results_modified_model.csv", index=False)
        print("Evaluation results saved to CSV file.")
        del model
        torch.cuda.empty_cache()
       Evaluating on validation set (Brightness=0.5):
       Accuracy: 0.778
       Precision: 0.983
       Recall: 0.567
       F1 Score: 0.719
```

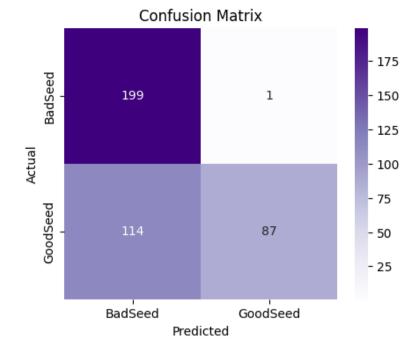
AUC Score: 0.917



transform_noise0_01 = create_transform(add_gaussian_noise, mean=0.0, std=0.01)
transform_noise0_05 = create_transform(add_gaussian_noise, mean=0.0, std=0.05)
transform_noise0_1 = create_transform(add_gaussian_noise, mean=0.0, std=0.1)

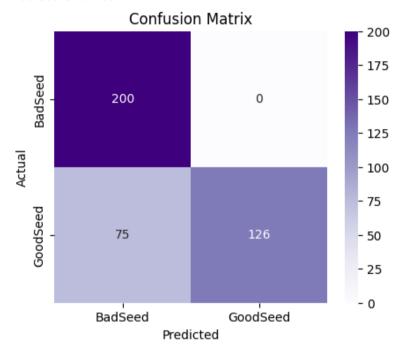
Evaluating on validation set (Brightness=1.5): Accuracy: 0.713 Precision: 0.989 Recall: 0.433

F1 Score: 0.602 AUC Score: 0.875



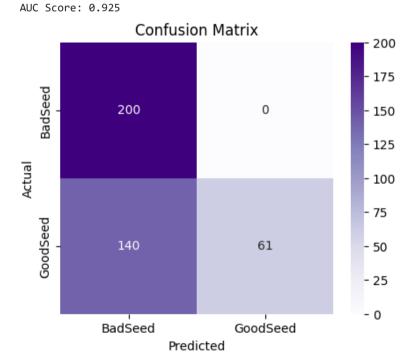
Evaluating on validation set (Noise=0.01):

Accuracy: 0.813 Precision: 1.000 Recall: 0.627 F1 Score: 0.771 AUC Score: 0.960



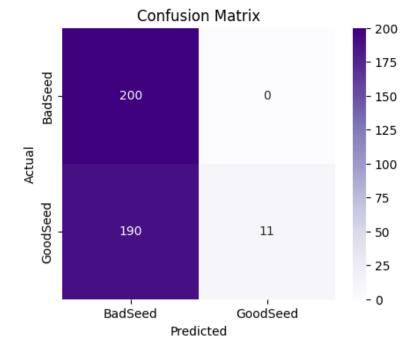
Evaluating on validation set (Noise=0.05):

Accuracy: 0.651 Precision: 1.000 Recall: 0.303 F1 Score: 0.466



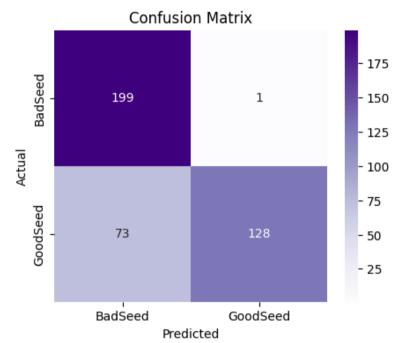
Evaluating on validation set (Noise=0.1):

Accuracy: 0.526 Precision: 1.000 Recall: 0.055 F1 Score: 0.104 AUC Score: 0.815



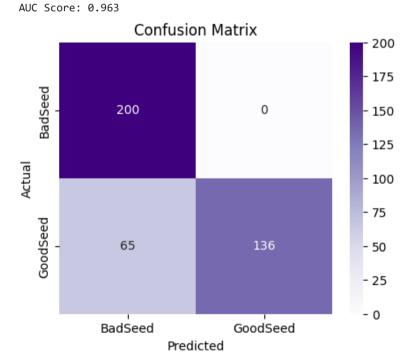
Evaluating on validation set (Scale=0.8):

Accuracy: 0.815 Precision: 0.992 Recall: 0.637 F1 Score: 0.776 AUC Score: 0.950



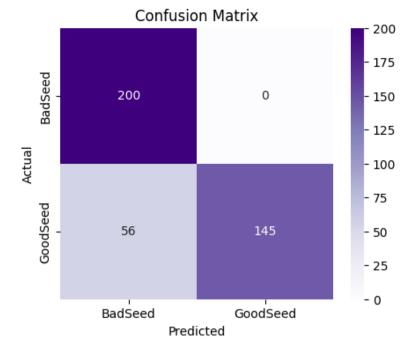
Evaluating on validation set (Scale=1.2):

Accuracy: 0.838 Precision: 1.000 Recall: 0.677 F1 Score: 0.807



Evaluating on validation set (Scale=1.5):

Accuracy: 0.860 Precision: 1.000 Recall: 0.721 F1 Score: 0.838 AUC Score: 0.967



Evaluating on validation set (Rotate=15):

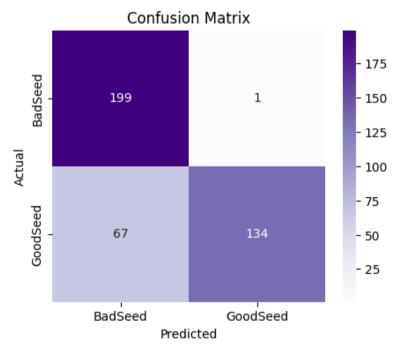
Accuracy: 0.830 Precision: 0.993 Recall: 0.667 F1 Score: 0.798 AUC Score: 0.961

Confusion Matrix - 175 BadSeed 199 1 - 150 - 125 Actual - 100 - 75 GoodSeed 67 - 50 - 25 GoodSeed BadSeed

Predicted

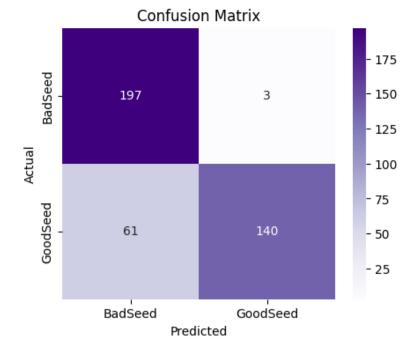
Evaluating on validation set (Rotate=30): Accuracy: 0.830

Precision: 0.993 Recall: 0.667 F1 Score: 0.798 AUC Score: 0.961



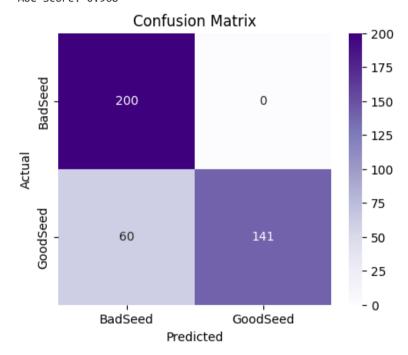
Evaluating on validation set (Rotate=45):

Accuracy: 0.840 Precision: 0.979 Recall: 0.697 F1 Score: 0.814 AUC Score: 0.965



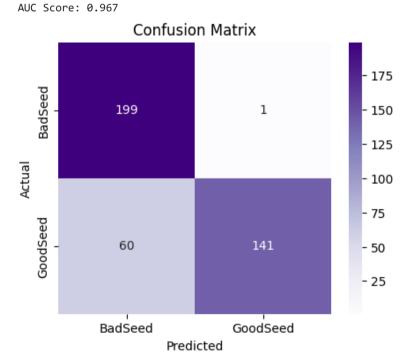
Evaluating on validation set (Rotate=90):

Accuracy: 0.850 Precision: 1.000 Recall: 0.701 F1 Score: 0.825 AUC Score: 0.968



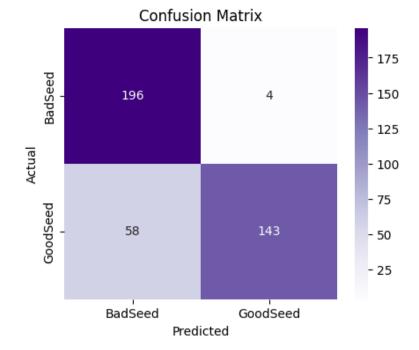
Evaluating on validation set (Rotate=180):

Accuracy: 0.848 Precision: 0.993 Recall: 0.701 F1 Score: 0.822



Evaluating on validation set (Rotate=360):

Accuracy: 0.845 Precision: 0.973 Recall: 0.711 F1 Score: 0.822 AUC Score: 0.963



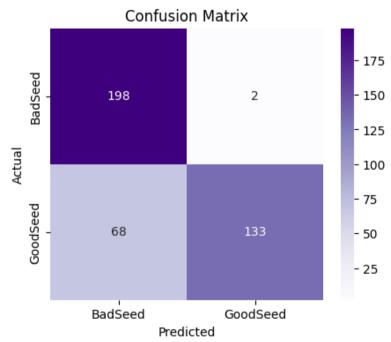
Evaluating on validation set (Translate=0.1):

Accuracy: 0.813 Precision: 0.992 Recall: 0.632 F1 Score: 0.772 AUC Score: 0.963

Confusion Matrix - 175 BadSeed 199 1 - 150 - 125 Actual - 100 - 75 GoodSeed 74 - 50 - 25 GoodSeed BadSeed Predicted

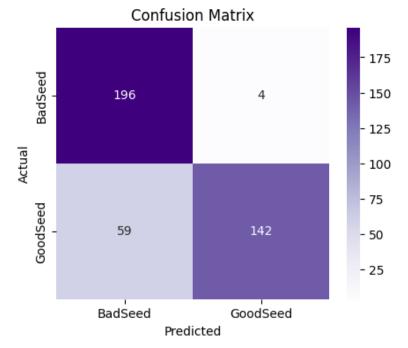
Evaluating on validation set (Translate=0.2):

Accuracy: 0.825 Precision: 0.985 Recall: 0.662 F1 Score: 0.792 AUC Score: 0.962



Evaluating on validation set (Translate=0.3):

Accuracy: 0.843 Precision: 0.973 Recall: 0.706 F1 Score: 0.818 AUC Score: 0.955



Evaluation results saved to CSV file.

tsne plots

Features Visualisation Across Different Layers

The following cell outputs the representation of the features at different layers of the model i.e. *conv1*, *inception3a*, *inception3b*, *inception4a*, *inception4c*, *inception5a*, *inception5b*, *avgpool*. This visualisation is used to discuss the results of Requirement 4.

```
import torch
In [ ]:
        from torch import nn
        from torchvision import transforms
        from torch.utils.data import DataLoader
        from tqdm import tqdm
        import numpy as np
        import matplotlib.pyplot as plt
        from sklearn.manifold import TSNE
        from torchvision.datasets import ImageFolder
        from torchvision.models import googlenet
        # dictionary to store the feature maps
        feature_maps = {}
        def get_activation(name):
            def hook(model, input, output):
                feature_maps[name] = output.detach()
            return hook
        device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
        model = googlenet(weights=None, aux_logits=False, init_weights=True)
        model.fc = nn.Linear(1024, 2) # modify classifier for 2 output classes
        state_dict = torch.load("/content/drive/MyDrive/Computer Vision Coursework/models/googlenet_trained_with_aug_modifications_batch1.pth")
        model.load_state_dict(state_dict)
        #select layers to hook
        layers_to_hook = {
            'early_conv': model.conv1,
            'early_inception': model.inception3a,
            'middle_inception': model.inception3b,
            'mid_deeper_inception': model.inception4a,
            'deeper_inception': model.inception4c,
            'even_deeper_inception': model.inception5a,
            'very_deep_inception': model.inception5b,
            'final_avgpool': model.avgpool,
        #attach hooks
        for name, layer in layers_to_hook.items():
            layer.register_forward_hook(get_activation(name))
        #remove the final classification layer for feature extraction
        model.fc = nn.Identity()
        model.to(device).eval()
        val_dir = "/content/drive/MyDrive/Computer Vision Coursework/seedsegment/test"
        # extracted from FinalNotebook1.ipynb
        mean = [0.5035, 0.5035, 0.4966]
        std = [0.2686, 0.2735, 0.2766]
        original_transform = transforms.Compose([
            transforms.Resize((299, 299)),
            transforms.ToTensor(),
            transforms.Normalize(mean=mean, std=std)
        ])
        val_dataset = ImageFolder(root=val_dir, transform=original_transform)
        val loader = DataLoader(val dataset, batch size=32, shuffle=False, num workers=2)
        all_features = {name: [] for name in layers_to_hook.keys()}
        all_labels = []
        #disable gradient computation
        with torch.no_grad():
            for images, labels in tqdm(val_loader, desc="Extracting Features"):
                images = images.to(device)
                labels = labels.to(device)
```

```
#store features from hooked layers
         for name in layers to hook.keys():
             feats = feature_maps[name]
             feats = feats.view(feats.size(0), -1)
             all_features[name].append(feats.cpu())
         all_labels.append(labels.cpu())
 #concatenate across batches
 for name in all_features.keys():
     all_features[name] = torch.cat(all_features[name], dim=0)
 all_labels = torch.cat(all_labels, dim=0)
 #run t-SNE and plot
 def plot_tsne(features, labels, title, ax):
     features = features.numpy()
     labels = labels.numpy()
     tsne = TSNE(n_components=2, random_state=42, perplexity=30)
     features 2d = tsne.fit transform(features)
     good_indices = labels == 1
     bad_indices = labels == 0
     ax.scatter(features_2d[bad_indices, 0], features_2d[bad_indices, 1],
                 c='red', label='Bad Seed', alpha=0.6)
     ax.scatter(features\_2d[good\_indices,\ 0],\ features\_2d[good\_indices,\ 1],
                 c='green', label='Good Seed', alpha=0.6)
     ax.set_title(f"{title} - t-SNE")
     ax.set_xlabel("Dim 1")
     ax.set_ylabel("Dim 2")
     ax.grid(True)
     ax.set_xlim(-40, 50)
     ax.set_ylim(-20, 15)
 fig, axes = plt.subplots(2, 4, figsize=(20, 10))
 axes = axes.flatten()
 for idx, (name, features) in enumerate(all_features.items()):
     plot_tsne(features, all_labels, title=name.replace("_", " ").title(), ax=axes[idx])
 handles, labels = axes[0].get_legend_handles_labels()
 fig.legend(handles, labels, loc='upper right')
 plt.tight_layout()
 plt.show()
 del model
 torch.cuda.empty_cache()
Extracting Features: 100% | 13/13 [00:07<00:00, 1.78it/s]
                                                                                                                                            Mid Deeper Inception - t-S
                Early Conv - t-SNE
                                                         Early Inception - t-SNE
                                                                                                   Middle Inception - t-SNE
  10
                                            10
                                                                                       10
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                                                                                                                                 -10
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 0 10
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                                                                                                                                                           20
                                                               Dim 1
                                                                                                         Dim 1
                                                      Even Deeper Inception - t-SNE
             Deeper Inception - t-SNE
                                                                                                  Very Deep Inception - t-SNE
                                                                                                                                              Final Avgpool - t-SNE
  15
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-40
                                                                                            -30
                                                                                                             10
                                                  -30
                                                                              40
                                                                                                -20
```

outputs = model(images)