workingmodel

November 7, 2024

```
[1]: # Step 1: Mount Google Drive
     from google.colab import drive
     drive.mount('/content/drive')
     # Step 2: Set up Dataset Paths in Google Drive
     train_path = "/content/drive/My Drive/dataset noise/train"
     val_path = "/content/drive/My Drive/dataset noise/valid"
     test_path = "/content/drive/My Drive/dataset noise/test"
     # Step 3: Import Libraries
     from sklearn.metrics import precision_score, recall_score, accuracy_score
     import torch
     import torch.nn as nn
     import torch.optim as optim
     import torch.nn.functional as F
     from torchvision import transforms, datasets
     from torch.utils.data import DataLoader, Dataset
     from tqdm import tqdm
     import matplotlib.pyplot as plt
     import numpy as np
     from skimage import color, measure, img_as_float
     from PIL import Image
     import os
```

Mounted at /content/drive

```
self.transform = transform
       self.image files = [f for f in os.listdir(image folder) if f.endswith('.
 →jpg')]
   def __len__(self):
       return len(self.image files)
   def getitem (self, idx):
        image_path = os.path.join(self.image_folder, self.image_files[idx])
        image = Image.open(image_path).convert("RGB")
        # Load corresponding label file
       label_name = f"{os.path.splitext(self.image_files[idx])[0]}.txt"
       label_path = os.path.join(self.label_folder, label_name)
        # Read label contents
       with open(label_path, 'r') as label_file:
            label_data = label_file.read() # Adjust this if your label file_
 ⇔has a specific structure
       if self.transform:
            image = self.transform(image)
       return image, label_data
# Define paths for train, val, and test data
train image path = os.path.join(train path, "images")
train_label_path = os.path.join(train_path, "labels")
val_image_path = os.path.join(val_path, "images")
val_label_path = os.path.join(val_path, "labels")
test_image_path = os.path.join(test_path, "images")
test_label_path = os.path.join(test_path, "labels")
# Create datasets and dataloaders
train_data = ImageLabelDataset(train_image_path, train_label_path,_

→transform=transform)
val_data = ImageLabelDataset(val_image_path, val_label_path,__
 test_data = ImageLabelDataset(test_image_path, test_label_path,__
 ⇔transform=transform)
train_loader = DataLoader(train_data, batch_size=8, shuffle=True, num_workers=2)
val_loader = DataLoader(val_data, batch_size=8, shuffle=False, num_workers=2)
test_loader = DataLoader(test_data, batch_size=8, shuffle=False, num_workers=2)
```

```
[3]: # High-Low Frequency Separation
     class HighLowFrequencySeparation:
         def __init__(self, kernel_size=5, sigma=1.5):
             self.gaussian_blur = transforms.GaussianBlur(kernel_size=kernel_size,_
      ⇒sigma=sigma)
         def separate(self, image):
             low_freq = self.gaussian_blur(image)
             high_freq = torch.abs(image - low_freq)
             return high_freq, low_freq
     # ConvGroup Module
     class ConvGroup(nn.Module):
         def __init__(self, in_channels):
             super(ConvGroup, self).__init__()
             self.conv = nn.Conv2d(in_channels, in_channels, kernel_size=3,__
      →padding=1, groups=in_channels)
             self.bn = nn.BatchNorm2d(in_channels)
             self.dwconv = nn.Conv2d(in_channels, in_channels, kernel_size=3,__
      →padding=1, groups=in_channels)
         def forward(self, x):
             out = F.relu(self.bn(self.conv(x)))
             out = F.relu(self.bn(self.dwconv(out)))
             return out + x
     # CrossAttention Module
     class CrossAttention(nn.Module):
         def __init__(self, in_channels, r=4):
             super(CrossAttention, self).__init__()
             self.pool_avg = nn.AdaptiveAvgPool2d(1)
             self.pool_max = nn.AdaptiveMaxPool2d(1)
             intermediate_channels = max(1, in_channels // r)
             self.fc1 = nn.Conv2d(in_channels, intermediate_channels, 1)
             self.fc2 = nn.Conv2d(intermediate_channels, in_channels, 1)
         def forward(self, x):
             avg = self.pool_avg(x)
             maxp = self.pool_max(x)
             avg out = self.fc2(F.relu(self.fc1(avg)))
             max_out = self.fc2(F.relu(self.fc1(maxp)))
             return avg_out * max_out + x
     # GCE Module
     class GCE(nn.Module):
         def __init__(self, in_channels):
             super(GCE, self).__init__()
```

```
self.conv_group = ConvGroup(in_channels)
        self.cross_attention = CrossAttention(in_channels)
   def forward(self, x):
       x = self.conv_group(x)
       x = self.cross_attention(x)
       return x
# ResidualBlock Module
class ResidualBlock(nn.Module):
   def __init__(self, in_channels):
        super(ResidualBlock, self).__init__()
        self.conv1 = nn.Conv2d(in_channels, in_channels, kernel_size=3,__
 →padding=1)
        self.inorm = nn.InstanceNorm2d(in_channels)
        self.prelu = nn.PReLU()
   def forward(self, x):
       out = self.prelu(self.inorm(self.conv1(x)))
       out = self.conv1(out)
       return out + x
# HHDNet Model
class HHDNet(nn.Module):
   def __init__(self, in_channels=3):
        super(HHDNet, self).__init__()
        self.high_low_sep = HighLowFrequencySeparation()
        self.high_freq_branch = nn.Sequential(
            *[GCE(in_channels) for _ in range(8)]
        self.low_freq_branch = nn.Sequential(
            *[ResidualBlock(in_channels) for _ in range(4)]
        )
        self.fusion = nn.Conv2d(in_channels * 2, in_channels, kernel_size=3,_
 ⇒padding=1)
   def forward(self, x):
       high_freq, low_freq = self.high_low_sep.separate(x)
       high_freq_out = self.high_freq_branch(high_freq)
        low_freq_out = self.low_freq_branch(low_freq)
        concat_out = torch.cat([high_freq_out, low_freq_out], dim=1)
        return self.fusion(concat_out) + x
```

```
[4]: import torch.nn.functional as F

def calculate_psnr(target, output):
    # Ensure MSE is calculated appropriately for better range control
```

```
mse = F.mse_loss(output, target)
if mse == 0:
    return 100
return 20 * torch.log10(1.0 / torch.sqrt(mse))

# Optionally, introduce a perceptual loss or SSIM for enhanced quality
```

```
[5]: def calculate_pixel_metrics(target, output, threshold=0.1):
    """
    Calculate pixel-wise precision, recall, and accuracy
    using a threshold for the pixel error.
    """

# Binarize images using the threshold
    target_bin = (target > threshold).cpu().numpy().flatten()
    output_bin = (output > threshold).cpu().numpy().flatten()

# Calculate precision, recall, accuracy
    precision = precision_score(target_bin, output_bin)
    recall = recall_score(target_bin, output_bin)
    accuracy = accuracy_score(target_bin, output_bin)

return precision, recall, accuracy
```

```
[6]: import numpy as np
    from skimage import color
    def calculate_uciqe(output):
        output = unnormalize(output) # Unnormalize to bring values back between Ou
        output = output.permute(1, 2, 0).cpu().numpy() # Convert to numpy
        contrast = np.std(output)
        mean_saturation = np.mean(color.rgb2hsv(output)[:, :, 1])
        std_hue = np.std(color.rgb2hsv(output)[:, :, 0])
        return 0.4680 * contrast + 0.2745 * mean_saturation + 0.2576 * std hue
    def calculate uigm(output):
        output = unnormalize(output)
        output = output.permute(1, 2, 0).cpu().numpy()
        uicm = np.mean(color.rgb2lab(output)[:, :, 1:3]) # Colorfulness
        uism = np.std(output) # Sharpness
        uiconm = np.mean(output) # Contrast
        return 0.0282 * uicm + 0.2953 * uism + 3.5753 * uiconm
```

```
[7]: import torch.nn as nn

class Discriminator(nn.Module):
    def __init__(self):
```

```
super(Discriminator, self).__init__()
       self.main = nn.Sequential(
           # input is (nc) x 64 x 64
           nn.Conv2d(3, 64, 4, 2, 1, bias=False),
           nn.LeakyReLU(0.2, inplace=True),
           # state size. (ndf) x 32 x 32
           nn.Conv2d(64, 128, 4, 2, 1, bias=False),
           nn.BatchNorm2d(128),
           nn.LeakyReLU(0.2, inplace=True),
           # state size. (ndf*2) x 16 x 16
           nn.Conv2d(128, 256, 4, 2, 1, bias=False),
           nn.BatchNorm2d(256),
           nn.LeakyReLU(0.2, inplace=True),
           # state size. (ndf*4) x 8 x 8
           nn.Conv2d(256, 512, 4, 2, 1, bias=False), # Reduced kernel size to_
\hookrightarrow 3x3
          nn.BatchNorm2d(512),
           nn.LeakyReLU(0.2, inplace=True),
           # state size. (ndf*8) x 4 x 4
           nn.Conv2d(512, 1, 3, 1, 1, bias=False), # Reduced kernel size to_
\rightarrow 3x3, Adjusted padding to 1
           # state size. 1 x 4 x 4 (or smaller based on other changes)
      self.pool = nn.AdaptiveAvgPool2d((1, 1)) #changed here
      self.flatten = nn.Flatten()
  def forward(self, x):
      x = self.main(x)
      x = self.pool(x) #changed here
      x = self.flatten(x)
      return x
  def __init__(self):
       super(Generator, self).__init__()
       self.encoder = nn.Sequential(
           nn.Conv2d(3, 64, kernel_size=4, stride=2, padding=1),
```

```
[8]: class Generator(nn.Module):
    def __init__(self):
        super(Generator, self).__init__()
        self.encoder = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=4, stride=2, padding=1),
            nn.ReLU(True),
            nn.Conv2d(64, 128, kernel_size=4, stride=2, padding=1),
            nn.ReLU(True),
            nn.Conv2d(128, 256, kernel_size=4, stride=2, padding=1),
            nn.ReLU(True),
        )
        self.middle = nn.Sequential(
            nn.Conv2d(256, 512, kernel_size=4, stride=2, padding=1),
            nn.ReLU(True),
        )
```

```
nn.Conv2d(512, 1024, kernel_size=4, stride=2, padding=1),
        nn.ReLU(True),
    )
    self.decoder = nn.Sequential(
        nn.ConvTranspose2d(1024, 512, kernel_size=4, stride=2, padding=1),
        nn.ReLU(True),
        nn.ConvTranspose2d(512, 256, kernel_size=4, stride=2, padding=1),
        nn.ReLU(True),
        nn.ConvTranspose2d(256, 128, kernel_size=4, stride=2, padding=1),
        nn.ReLU(True),
        nn.ConvTranspose2d(128, 3, kernel_size=4, stride=2, padding=1),
       nn.Tanh() # Output in range [-1, 1]
    )
def forward(self, x):
   x = self.encoder(x)
   x = self.middle(x)
   x = self.decoder(x)
    return x
```

```
[9]: # Training Function
     def train_model(generator, discriminator, train_loader, optimizer_G,_
      ⇔optimizer_D, criterion, num_epochs=10, device='cuda'):
         generator.train()
         discriminator.train()
         for epoch in range(num_epochs):
             total_g_loss = 0
             total d loss = 0
             for images, _ in tqdm(train_loader):
                 images = images.to(device)
                 # Train Discriminator
                 optimizer_D.zero_grad()
                 real_labels = torch.ones((images.size(0), 1), device=device)
                 fake_labels = torch.zeros((images.size(0), 1), device=device)
                 # Discriminator Loss on Real Images
                 outputs = discriminator(images)
                 d_loss_real = criterion(outputs, real_labels)
                 # Discriminator Loss on Fake Images
                 fake_images = generator(images)
                 outputs = discriminator(fake images.detach())
                 d_loss_fake = criterion(outputs, fake_labels)
```

```
# Total Discriminator Loss
                  d_loss = d_loss_real + d_loss_fake
                  d_loss.backward()
                  optimizer_D.step()
                  # Train Generator
                  optimizer_G.zero_grad()
                  outputs = discriminator(fake_images)
                  g_loss = criterion(outputs, real_labels)
                  g_loss.backward()
                  optimizer_G.step()
                  total_g_loss += g_loss.item()
                  total_d_loss += d_loss.item()
              print(f"Epoch [{epoch+1}/{num_epochs}], Generator Loss: {total_g_loss/
       -len(train_loader):.4f}, Discriminator Loss: {total_d_loss/len(train_loader):.
       <4f}")
[10]: def calc_gradient_penalty(D, real_samples, fake_samples, lambda_gp=10):
          # Experiment with a lower lambda_gp
          lambda_gp = 5 # Adjust this value
          return gradient_penalty
[11]: # Validation Function
      def validate_model(generator, val_loader, device='cuda'):
          generator.eval()
          avg_psnr = 0
          avg precision = 0
          avg_recall = 0
          avg_accuracy = 0
          avg_uciqe = 0
          num_samples = 0
          with torch.no_grad():
              for images, _ in tqdm(val_loader):
                  images = images.to(device)
                  outputs = generator(images)
                  # Calculate PSNR
                  psnr = calculate_psnr(images, outputs)
                  avg_psnr += psnr
                  # Calculate pixel-based metrics
                  precision, recall, accuracy = calculate_pixel_metrics(images,__
       →outputs)
```

```
avg_precision += precision
                  avg_recall += recall
                  avg_accuracy += accuracy
                  # Calculate UCIQE
                  uciqe = calculate_uciqe(outputs[0])
                  avg_uciqe += uciqe
                  num_samples += 1
          avg_psnr /= num_samples
          avg precision /= num samples
          avg_recall /= num_samples
          avg_accuracy /= num_samples
          avg_uciqe /= num_samples
          print(f"Validation PSNR: {avg_psnr:.4f}, Precision: {avg_precision:.4f}, u
       Recall: {avg_recall:.4f}, Accuracy: {avg_accuracy:.4f}, UCIQE: {avg_uciqe:.
       <4f}")
[12]: # Initialize Models
      device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
      generator = HHDNet().to(device)
      discriminator = Discriminator().to(device)
      # Optimizers
      optimizer_G = optim.Adam(generator.parameters(), lr=0.0001, betas=(0.5, 0.999))
      optimizer_D = optim.Adam(discriminator.parameters(), lr=0.0001, betas=(0.5, 0.
       →999))
      # Loss Function
      criterion = nn.BCEWithLogitsLoss()
[14]: # Train the Model# Reuse the previous train model function without changes
      num_epochs = 30  # Adjust based on your needs
      train_model(generator, discriminator, train_loader, optimizer_G, optimizer_D, u
       ⇔criterion, num epochs, device)
     100%|
               | 471/471 [00:45<00:00, 10.28it/s]
     Epoch [1/30], Generator Loss: 5.5466, Discriminator Loss: 0.0548
                | 471/471 [00:44<00:00, 10.48it/s]
     Epoch [2/30], Generator Loss: 5.8618, Discriminator Loss: 0.0812
               | 471/471 [00:44<00:00, 10.48it/s]
     100%|
     Epoch [3/30], Generator Loss: 6.9920, Discriminator Loss: 0.0076
               | 471/471 [00:45<00:00, 10.43it/s]
     100%|
```

```
Epoch [4/30], Generator Loss: 6.4974, Discriminator Loss: 0.0737
```

100% | 471/471 [00:43<00:00, 10.85it/s]

Epoch [5/30], Generator Loss: 6.2151, Discriminator Loss: 0.1043

100% | 471/471 [00:44<00:00, 10.69it/s]

Epoch [6/30], Generator Loss: 6.0358, Discriminator Loss: 0.0708

100% | 471/471 [00:45<00:00, 10.40it/s]

Epoch [7/30], Generator Loss: 6.5207, Discriminator Loss: 0.0806

100% | 471/471 [00:45<00:00, 10.46it/s]

Epoch [8/30], Generator Loss: 6.3874, Discriminator Loss: 0.0620

100% | 471/471 [00:44<00:00, 10.63it/s]

Epoch [9/30], Generator Loss: 6.3038, Discriminator Loss: 0.0983

100% | 471/471 [00:44<00:00, 10.69it/s]

Epoch [10/30], Generator Loss: 6.4891, Discriminator Loss: 0.0848

100% | 471/471 [00:43<00:00, 10.79it/s]

Epoch [11/30], Generator Loss: 5.8032, Discriminator Loss: 0.1259

100% | 471/471 [00:43<00:00, 10.94it/s]

Epoch [12/30], Generator Loss: 6.1932, Discriminator Loss: 0.0832

100% | 471/471 [00:43<00:00, 10.75it/s]

Epoch [13/30], Generator Loss: 5.7267, Discriminator Loss: 0.1662

100% | 471/471 [00:44<00:00, 10.50it/s]

Epoch [14/30], Generator Loss: 5.2556, Discriminator Loss: 0.1975

100% | 471/471 [00:44<00:00, 10.60it/s]

Epoch [15/30], Generator Loss: 5.1214, Discriminator Loss: 0.1614

100% | 471/471 [00:44<00:00, 10.69it/s]

Epoch [16/30], Generator Loss: 4.4290, Discriminator Loss: 0.3107

100% | 471/471 [00:44<00:00, 10.62it/s]

Epoch [17/30], Generator Loss: 3.7789, Discriminator Loss: 0.3659

100% | 471/471 [00:43<00:00, 10.85it/s]

Epoch [18/30], Generator Loss: 3.4550, Discriminator Loss: 0.4290

100% | 471/471 [00:42<00:00, 11.05it/s]

Epoch [19/30], Generator Loss: 3.1589, Discriminator Loss: 0.4940

100% | 471/471 [00:43<00:00, 10.73it/s]

```
Epoch [21/30], Generator Loss: 2.1157, Discriminator Loss: 0.7782
               | 471/471 [00:45<00:00, 10.36it/s]
     Epoch [22/30], Generator Loss: 1.6909, Discriminator Loss: 0.8988
     100%|
               | 471/471 [00:44<00:00, 10.57it/s]
     Epoch [23/30], Generator Loss: 1.4601, Discriminator Loss: 1.0153
                | 471/471 [00:44<00:00, 10.56it/s]
     100%
     Epoch [24/30], Generator Loss: 1.3447, Discriminator Loss: 1.0350
     100%|
                | 471/471 [00:44<00:00, 10.69it/s]
     Epoch [25/30], Generator Loss: 1.2364, Discriminator Loss: 1.0897
     100%|
                | 471/471 [00:43<00:00, 10.83it/s]
     Epoch [26/30], Generator Loss: 1.1036, Discriminator Loss: 1.1678
     100%
                | 471/471 [00:43<00:00, 10.93it/s]
     Epoch [27/30], Generator Loss: 1.0223, Discriminator Loss: 1.1950
               | 471/471 [00:43<00:00, 10.77it/s]
     100%|
     Epoch [28/30], Generator Loss: 0.9187, Discriminator Loss: 1.2799
     100%|
                | 471/471 [00:44<00:00, 10.66it/s]
     Epoch [29/30], Generator Loss: 0.9058, Discriminator Loss: 1.2630
     100%|
                | 471/471 [00:43<00:00, 10.72it/s]
     Epoch [30/30], Generator Loss: 0.8623, Discriminator Loss: 1.3020
[15]: def unnormalize(image):
          # Ensure mean and std are on the same device as the image
          mean = torch.tensor([0.5, 0.5, 0.5], device=image.device).view(3, 1, 1)
          std = torch.tensor([0.5, 0.5, 0.5], device=image.device).view(3, 1, 1)
          return image * std + mean
[16]: # Validate the Model
      validate_model(generator, val_loader, device)
     100%|
               | 87/87 [04:40<00:00, 3.23s/it]
     Validation PSNR: 35.3715, Precision: 0.9991, Recall: 0.9503, Accuracy: 0.9916,
     UCIQE: 0.2389
```

Epoch [20/30], Generator Loss: 2.8948, Discriminator Loss: 0.5422

| 471/471 [00:45<00:00, 10.38it/s]

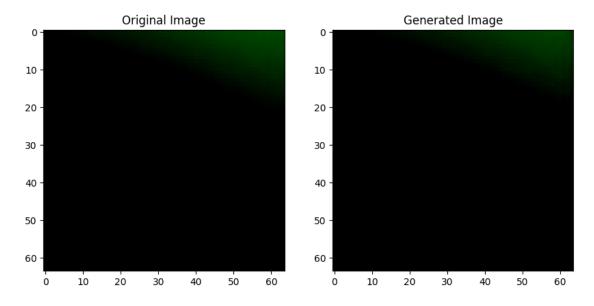
```
[]: # Save the trained models
      torch.save(generator.state_dict(), "/content/drive/My Drive/generator.pth")
      torch.save(discriminator.state_dict(), "/content/drive/My Drive/discriminator.
       ⇔pth")
      # To load the models later:
      # generator.load_state_dict(torch.load("/content/drive/My Drive/generator.pth"))
      # discriminator.load_state_dict(torch.load("/content/drive/My Drive/
       ⇔discriminator.pth"))
[17]: # Unnormalize helper function
      def unnormalize(image):
          # Assuming the mean and std from the data normalization transform
          mean = torch.tensor([0.5, 0.5, 0.5]).view(3, 1, 1).to(image.device) # Moveu
       ⇔mean to image's device
          std = torch.tensor([0.5, 0.5, 0.5]).view(3, 1, 1).to(image.device) # Move_{\perp}
       ⇔std to image's device
          return image * std + mean
[18]: import torch.nn.functional as F
      from sklearn.metrics import precision_score, recall_score, accuracy_score
      import matplotlib.pyplot as plt
      import numpy as np
      from skimage import color
      # Testing function with PSNR, Pixel-wise metrics, UCIQE, and UIQM
      def test_model(generator, test_loader, device='cuda'):
          generator.eval()
          total psnr = 0
          total_precision = 0
          total_recall = 0
          total accuracy = 0
          total_uciqe = 0
          total_uiqm = 0
          num_images = 0
          with torch.no_grad():
              for images, _ in test_loader:
                  images = images.to(device)
                  outputs = generator(images)
                  for i in range(len(images)):
                      original_img = images[i]
                      generated_img = outputs[i]
                      # Calculate metrics
                      psnr_value = calculate_psnr(original_img, generated_img)
```

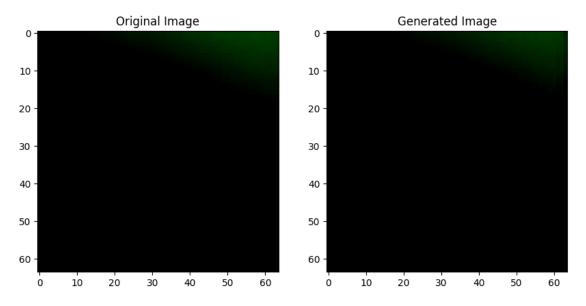
```
precision, recall, accuracy = ___
 ⇒calculate_pixel_metrics(original_img, generated_img)
                uciqe = calculate_uciqe(generated_img)
                uiqm = calculate_uiqm(generated_img)
                # Accumulate metrics for averaging
                total_psnr += psnr_value
                total_precision += precision
                total_recall += recall
                total_accuracy += accuracy
                total_uciqe += uciqe
                total_uiqm += uiqm
                num_images += 1
                # Display a few examples
                if i < 3: # Display up to 3 images</pre>
                    plt.figure(figsize=(10, 5))
                    # Display Original Image
                    plt.subplot(1, 2, 1)
                    plt.imshow(original_img.cpu().permute(1, 2, 0).numpy())
                    plt.title("Original Image")
                    # Display Generated Image
                    plt.subplot(1, 2, 2)
                    plt.imshow(generated_img.cpu().permute(1, 2, 0).numpy())
                    plt.title("Generated Image")
                    plt.show()
        # Calculate average metrics
        avg_psnr = total_psnr / num_images
        avg_precision = total_precision / num_images
       avg recall = total recall / num images
        avg_accuracy = total_accuracy / num_images
        avg_uciqe = total_uciqe / num_images
        avg_uiqm = total_uiqm / num_images
        # Print average metrics
       print(f"Average PSNR: {avg_psnr:.2f}")
       print(f"Average Precision: {avg_precision:.4f}")
       print(f"Average Recall: {avg_recall:.4f}")
        print(f"Average Accuracy: {avg_accuracy:.4f}")
       print(f"Average UCIQE: {avg_uciqe:.4f}")
       print(f"Average UIQM: {avg_uiqm:.4f}")
# Run the test model
```

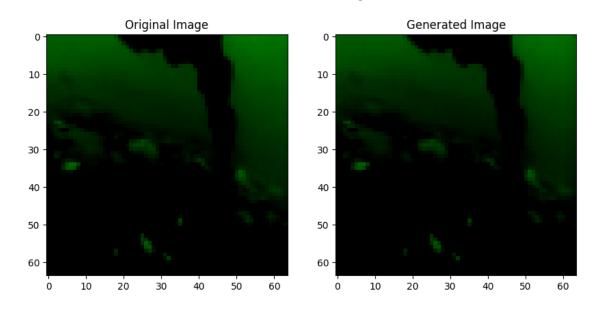
test_model(generator, test_loader, device)

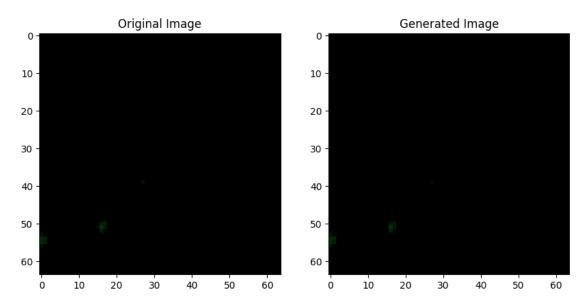
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

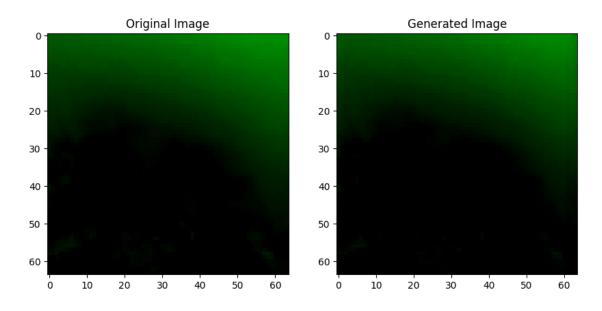
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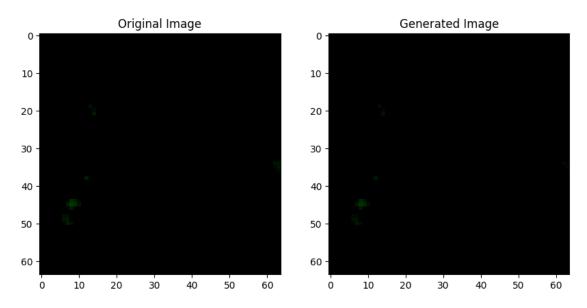


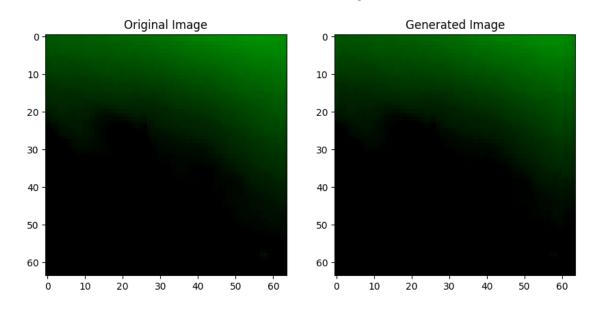


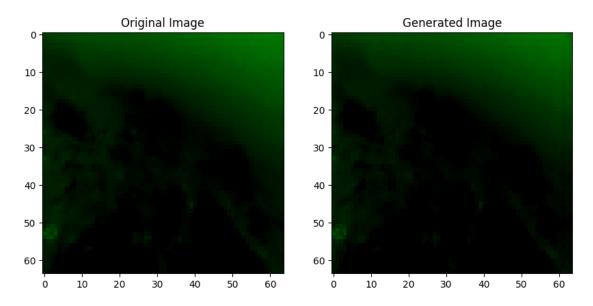


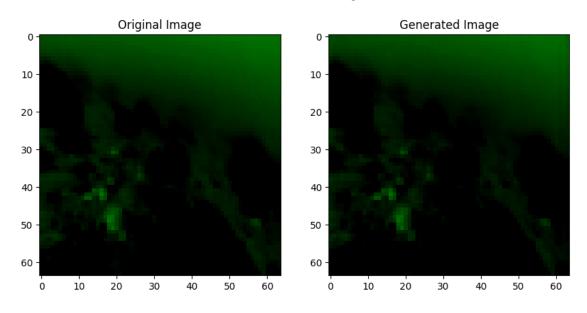










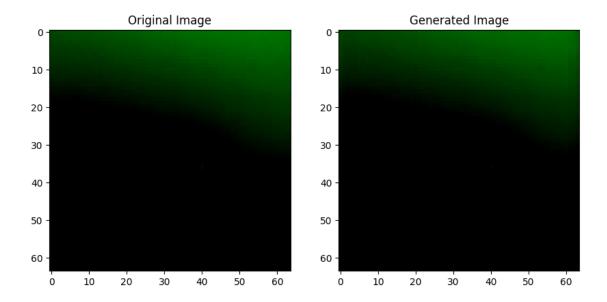


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.

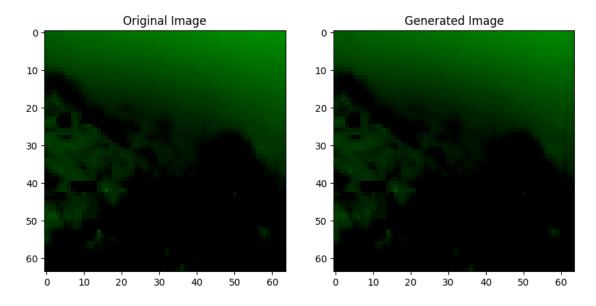
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
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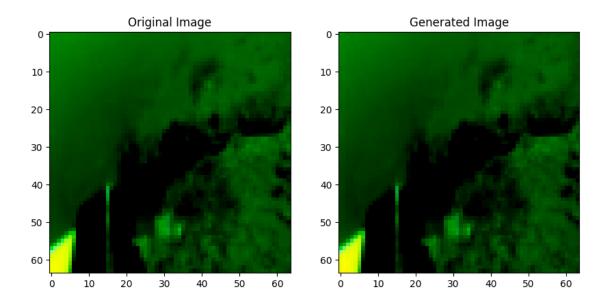
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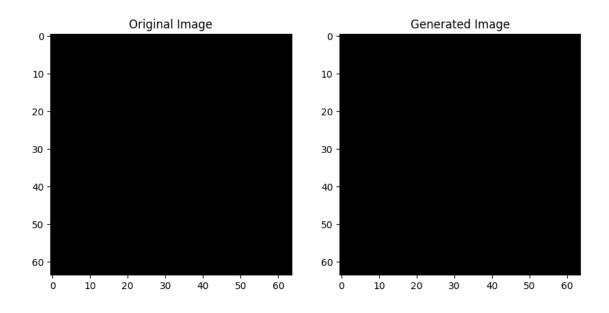
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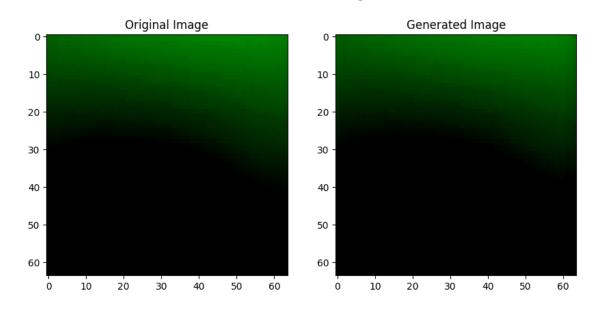


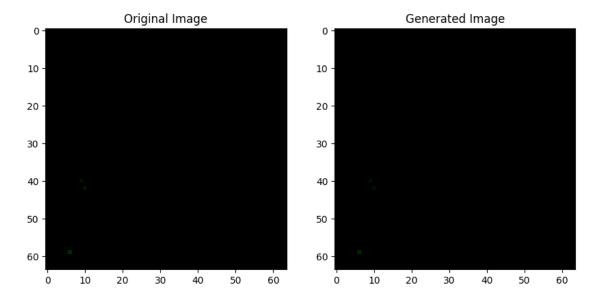
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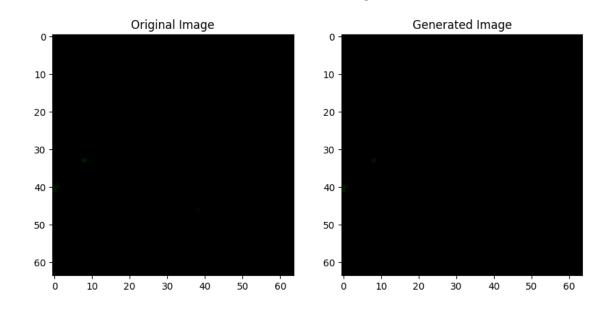


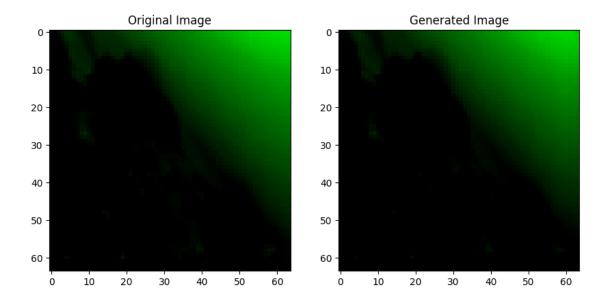
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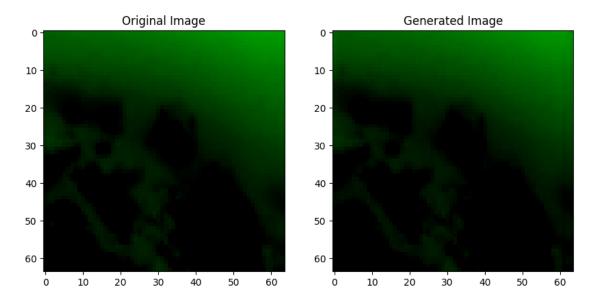
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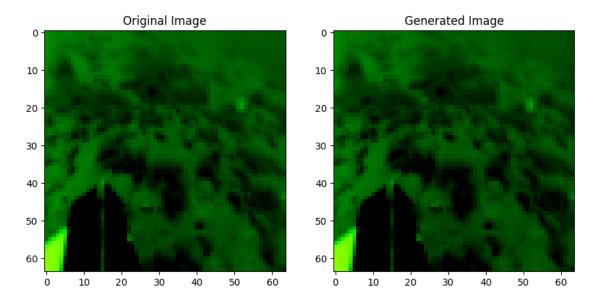


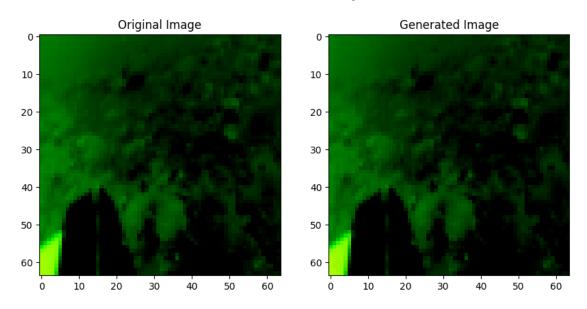
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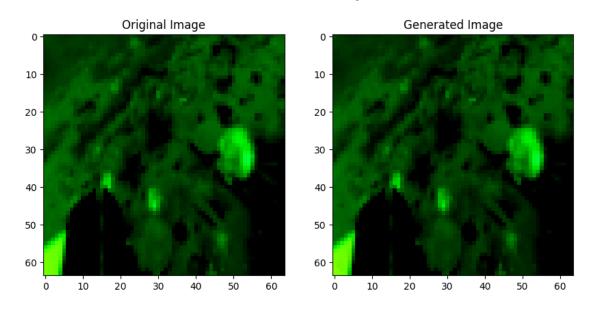
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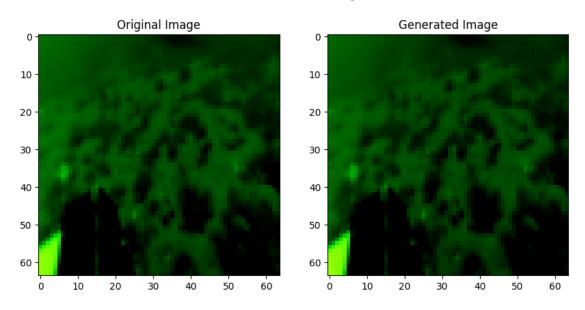
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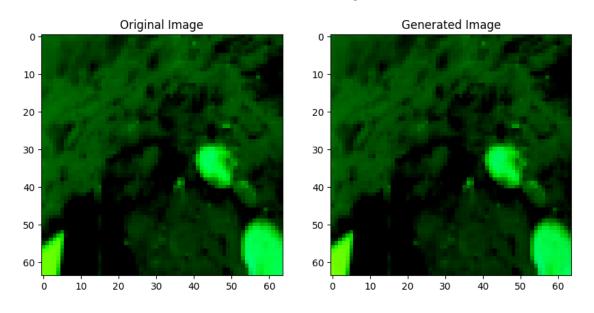
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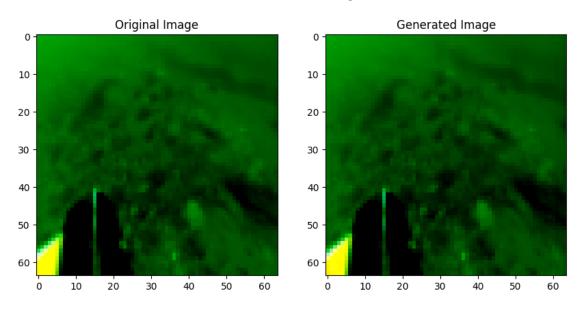


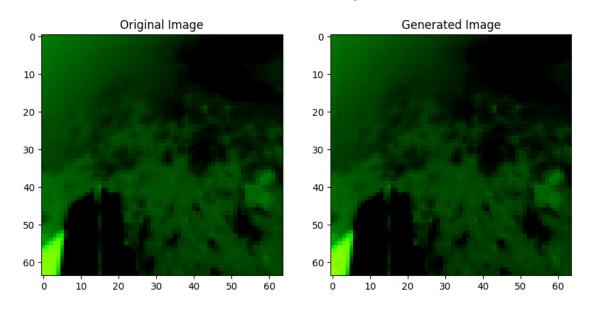




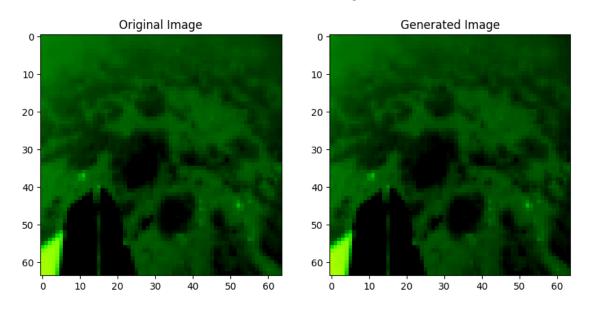


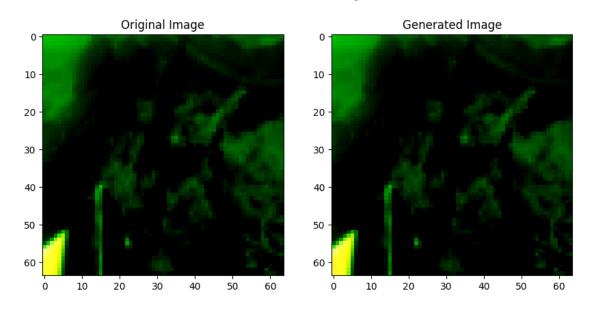


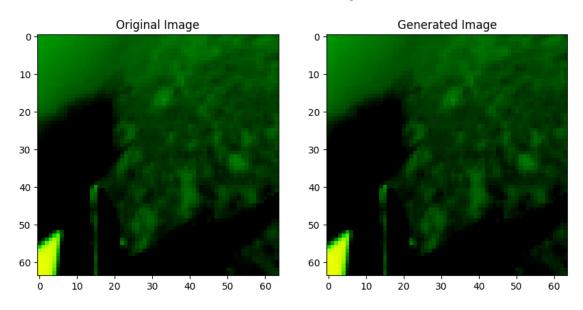


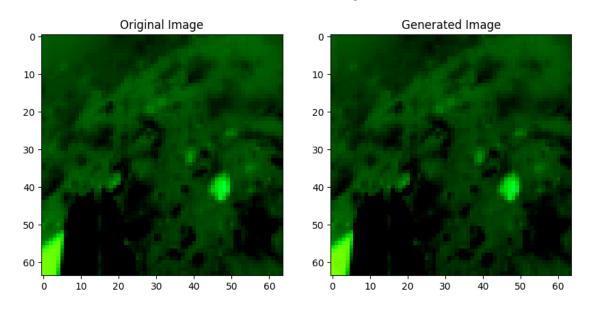


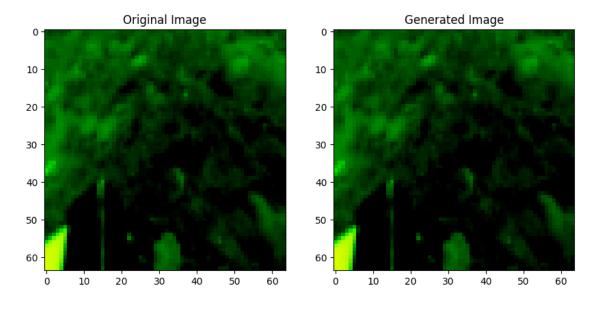
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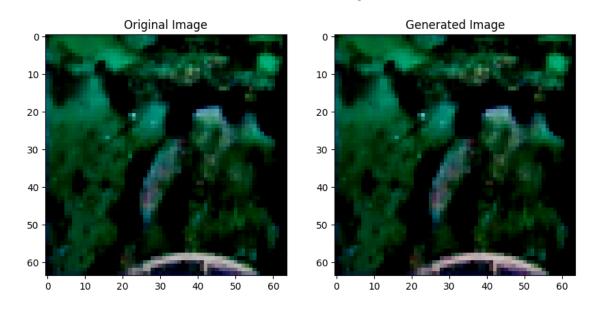


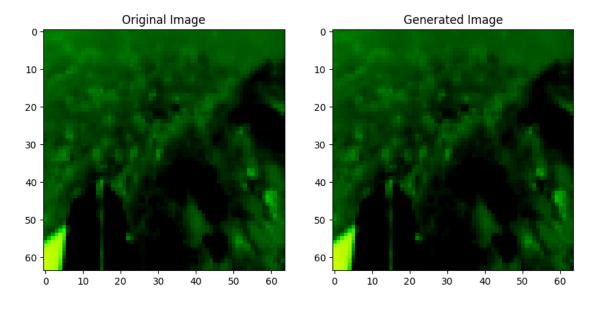


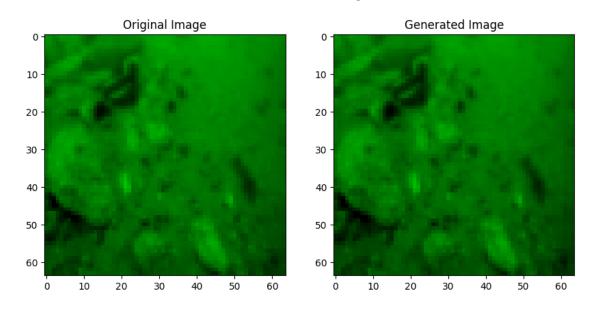


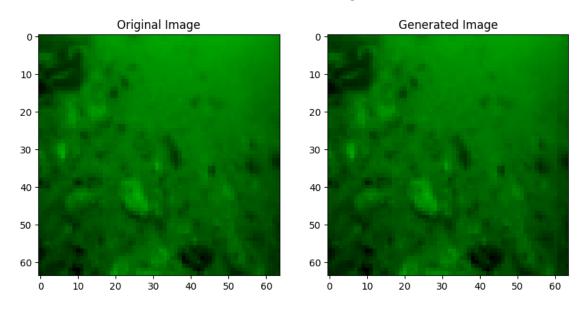


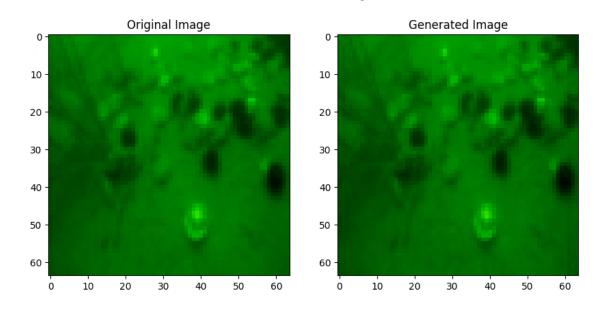


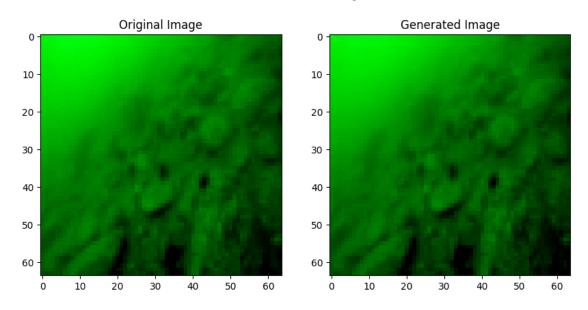


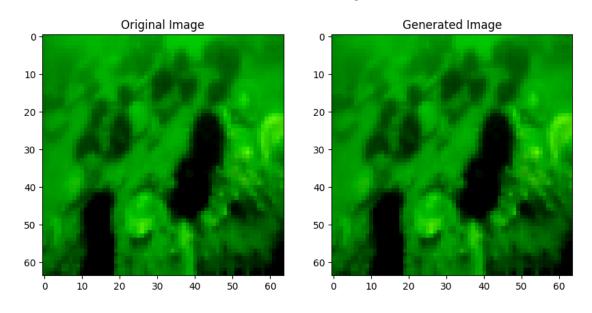


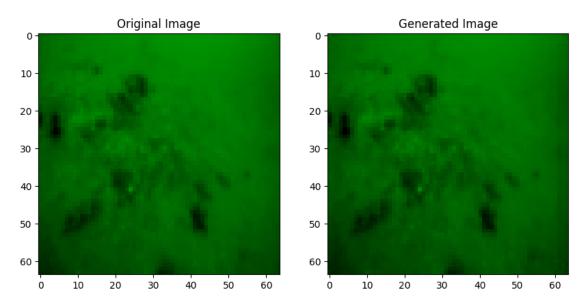


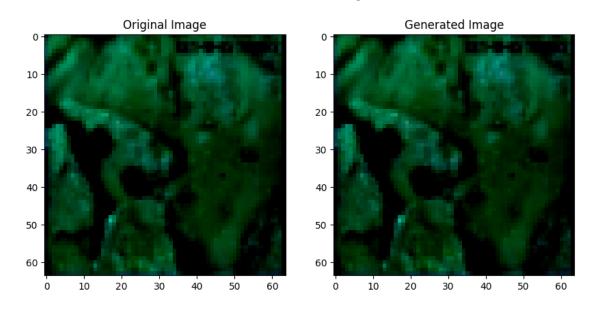


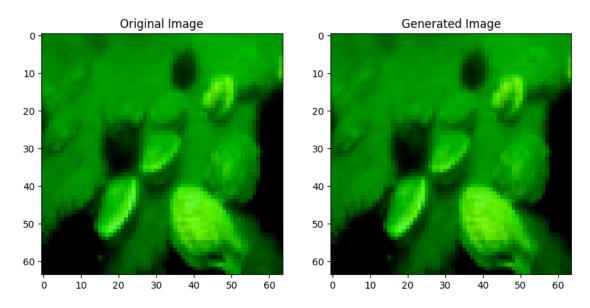


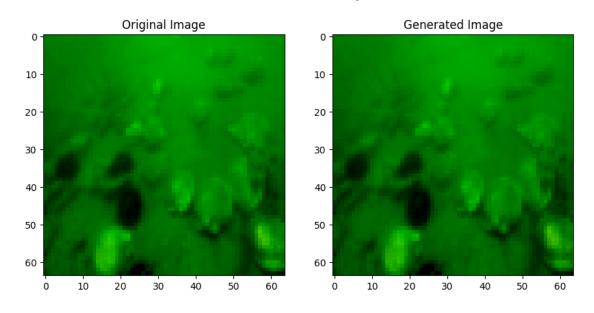


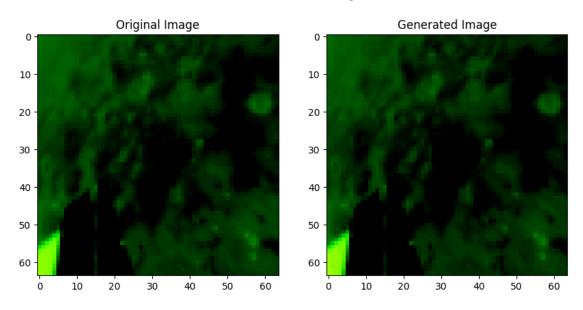


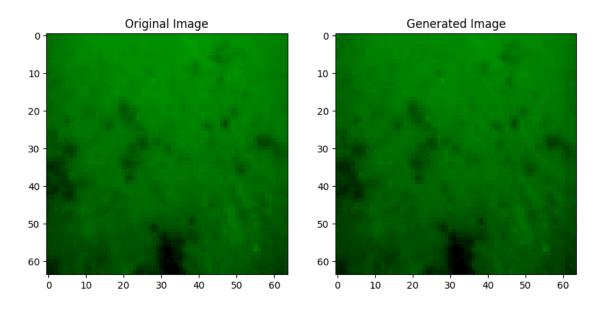


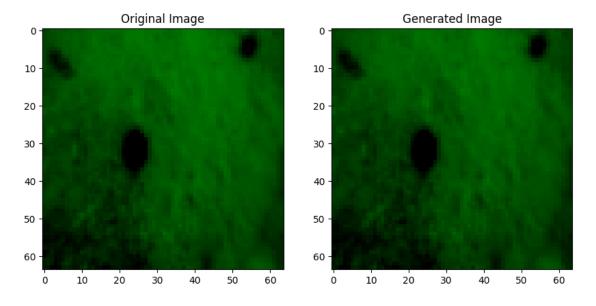


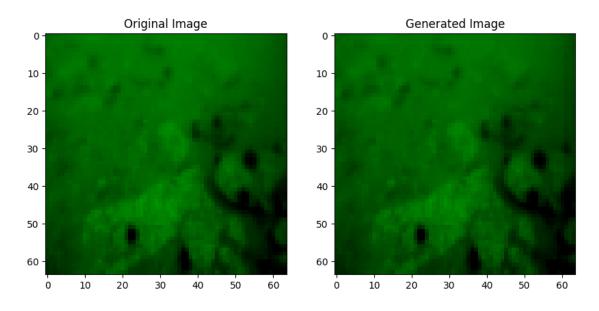


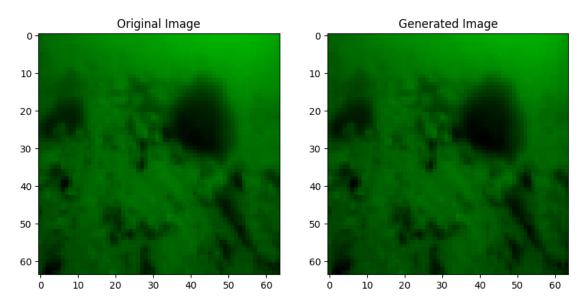


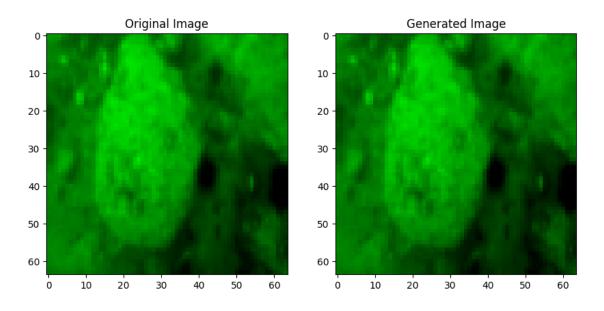


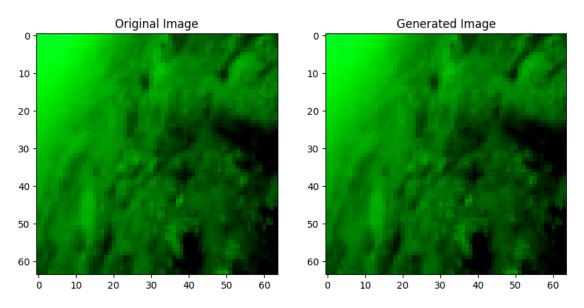


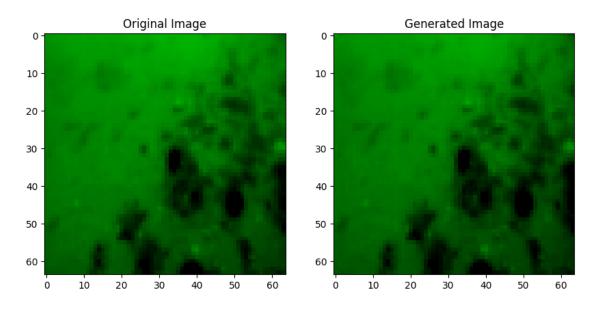


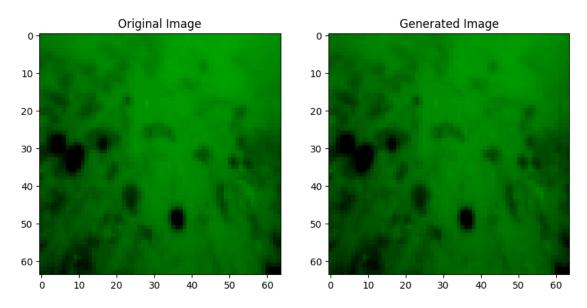


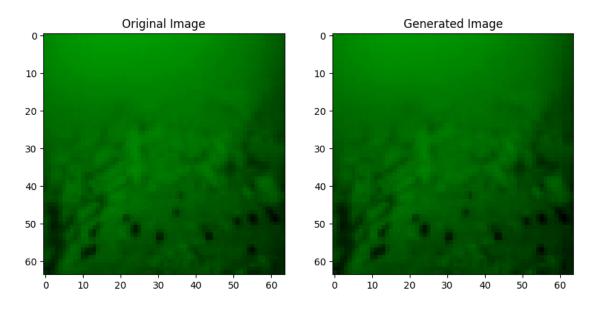


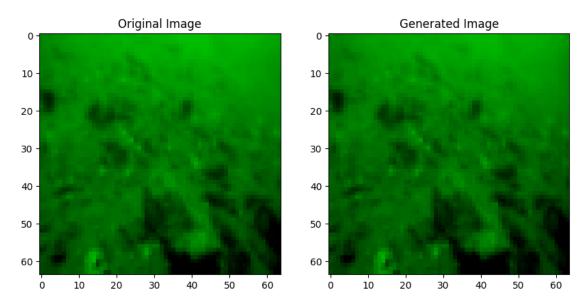


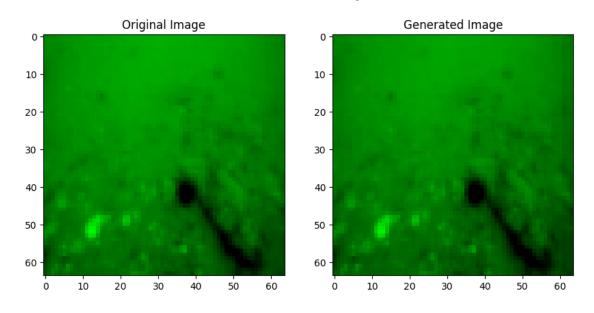


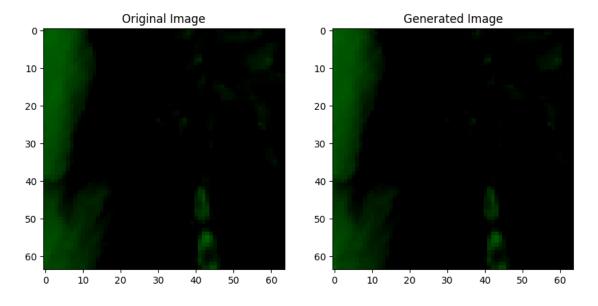


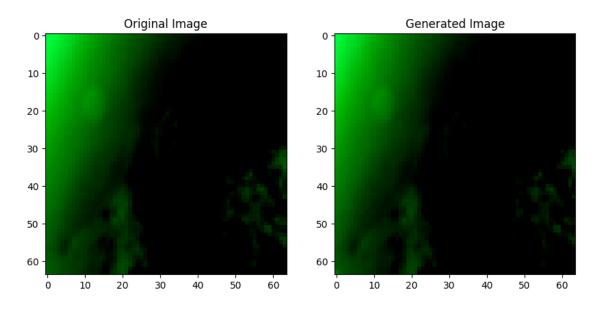


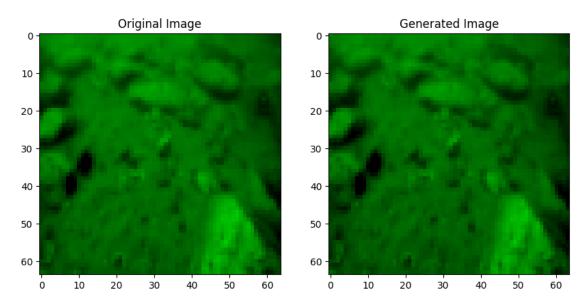


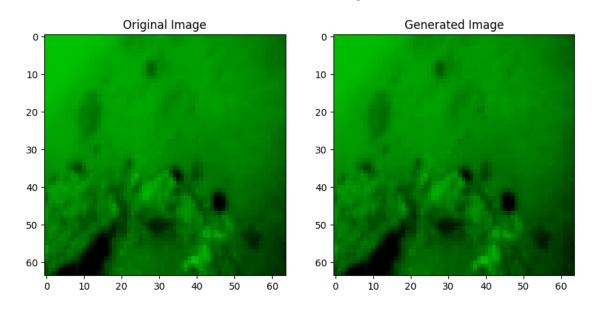


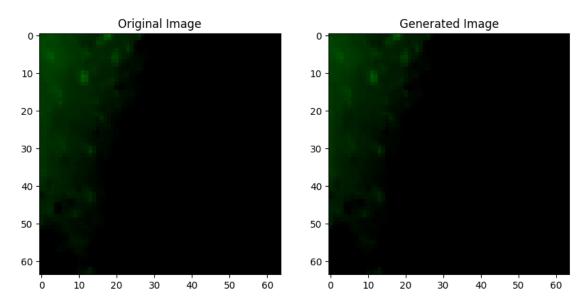


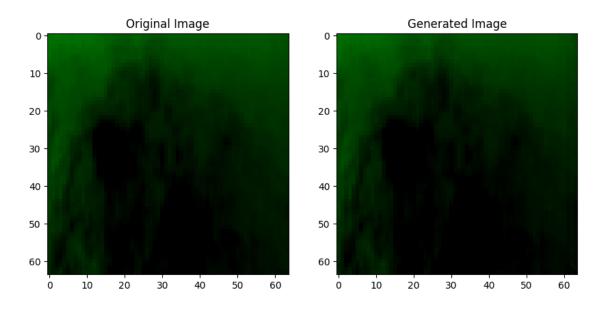


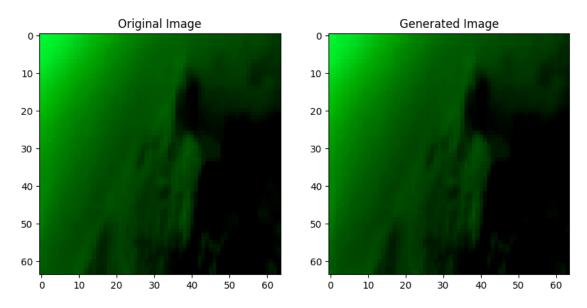


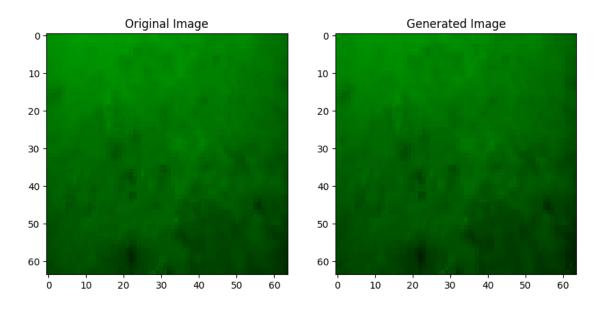


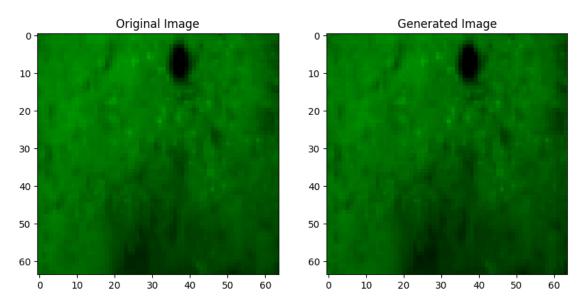


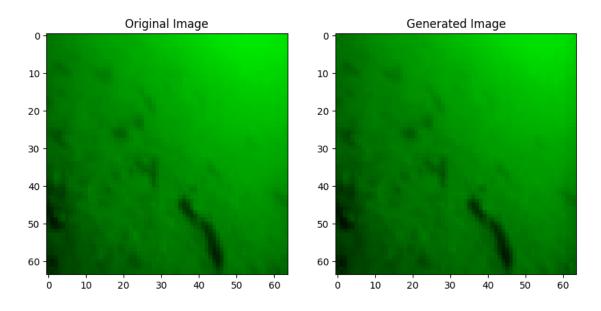


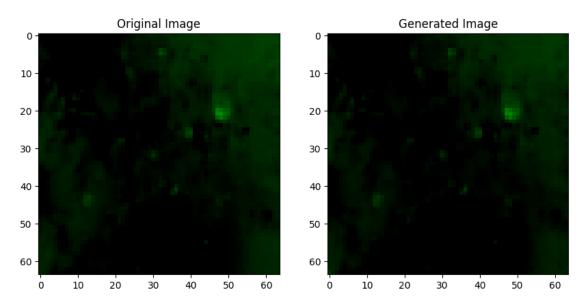


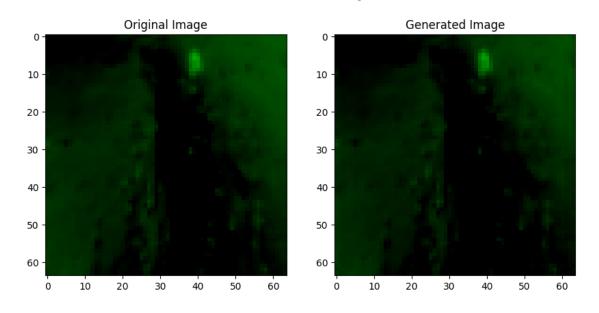


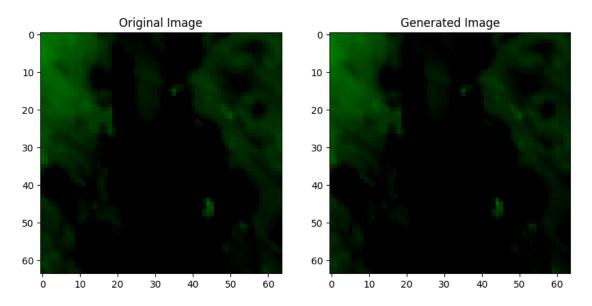








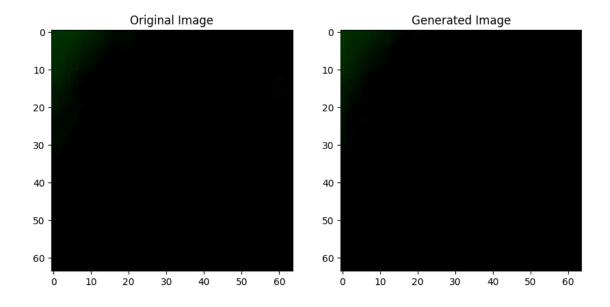


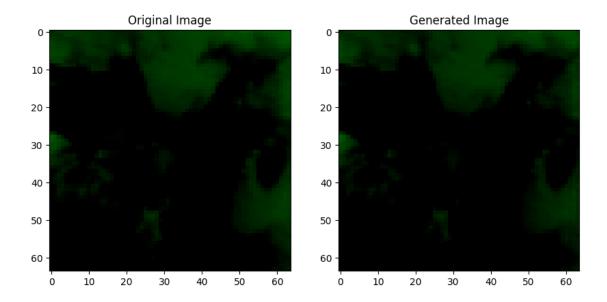


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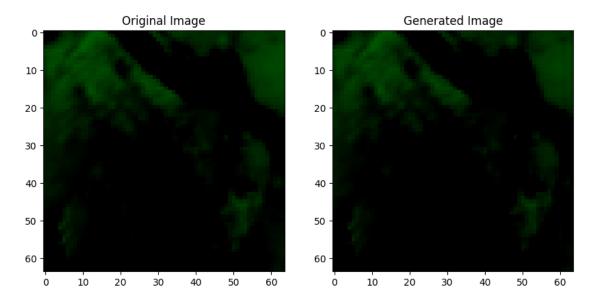
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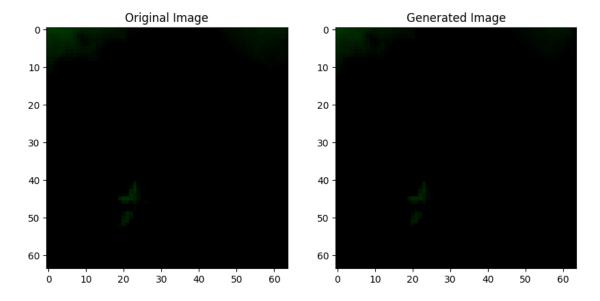


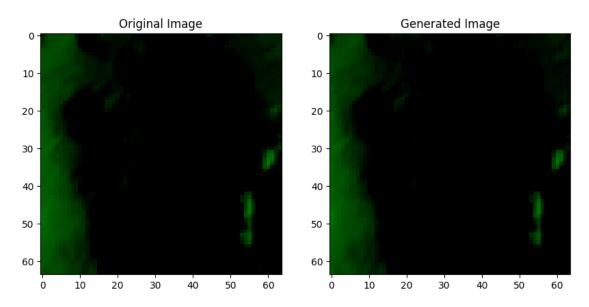
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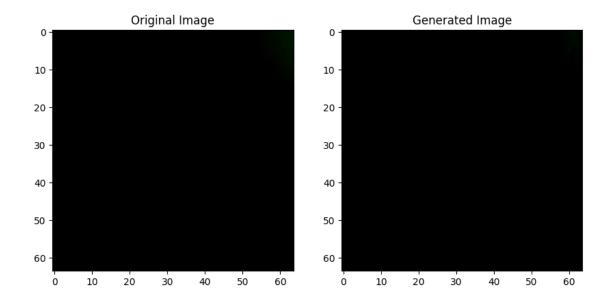


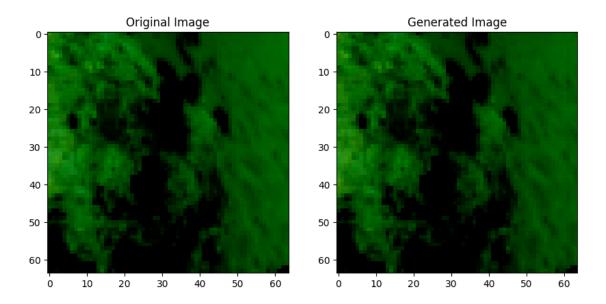


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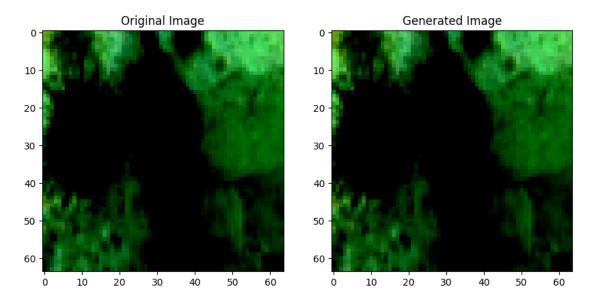
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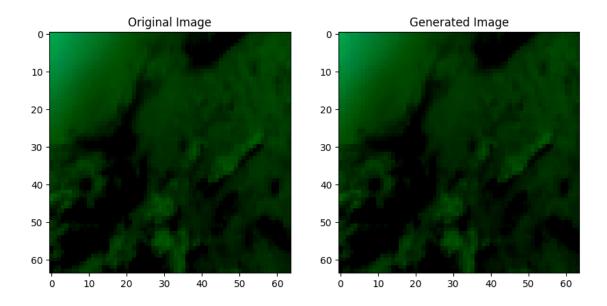




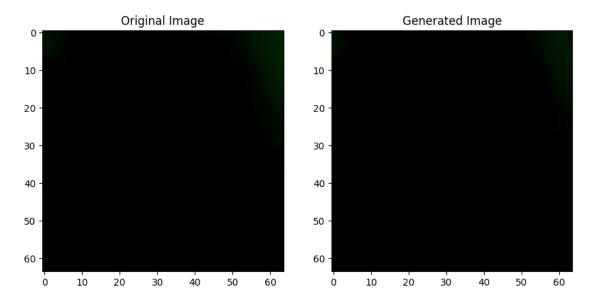
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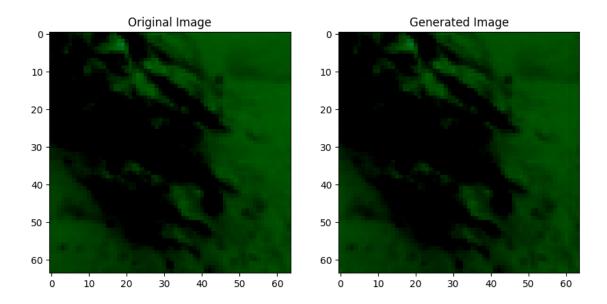
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WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



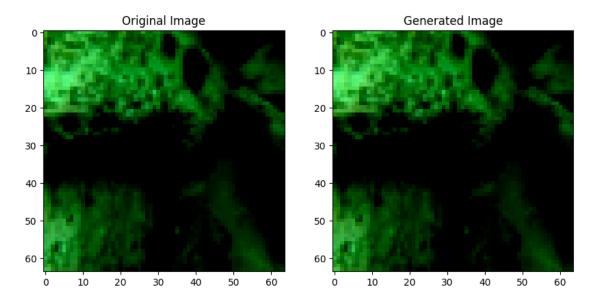
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



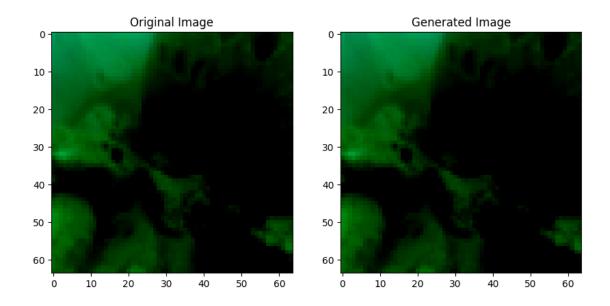
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



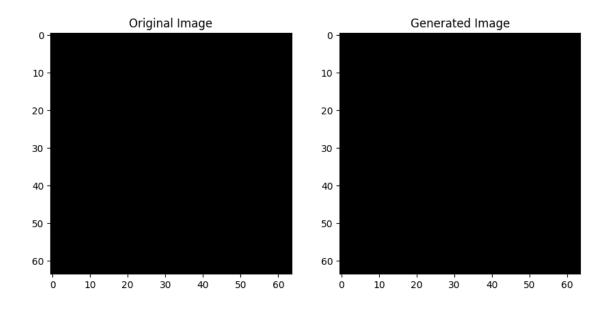
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

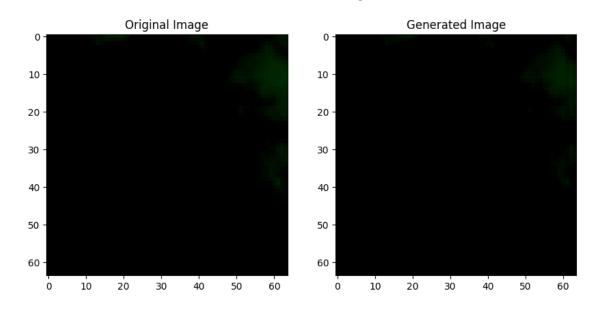


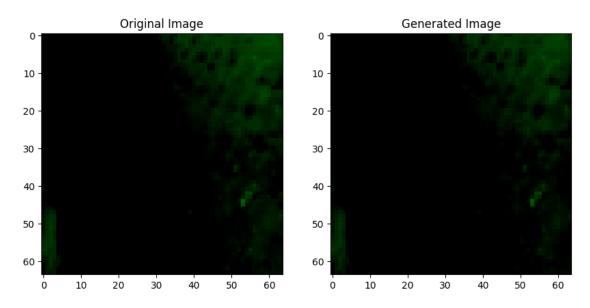
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.

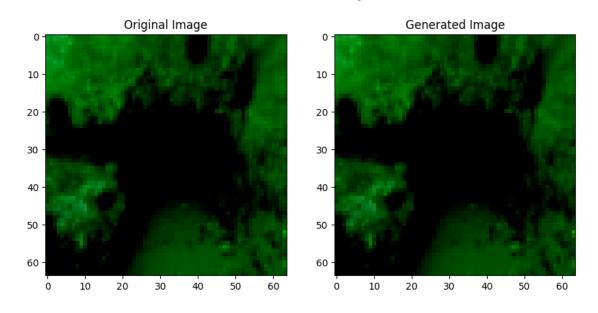
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531:
UndefinedMetricWarning: Recall is ill-defined and being set to 0.0 due to no
true samples. Use `zero_division` parameter to control this behavior.

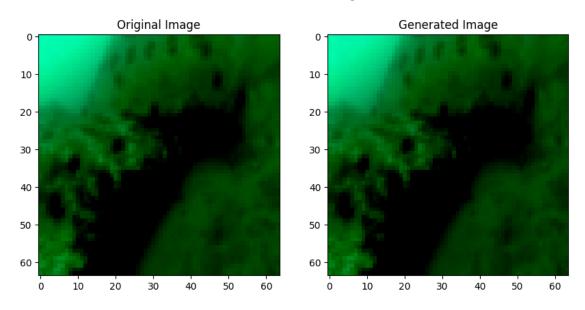
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with
RGB data ([0..1] for floats or [0..255] for integers).
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with
RGB data ([0..1] for floats or [0..255] for integers).

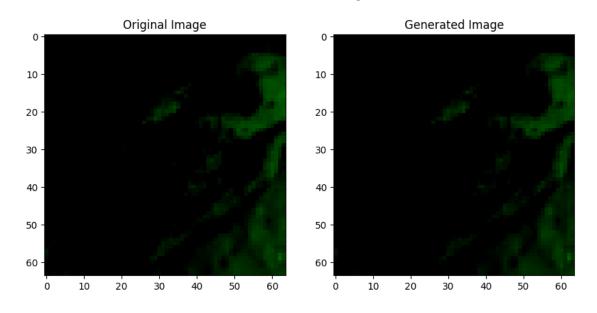


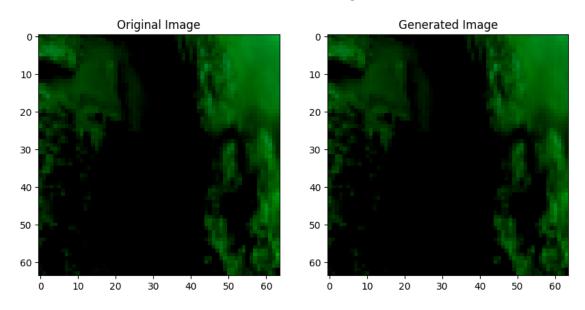


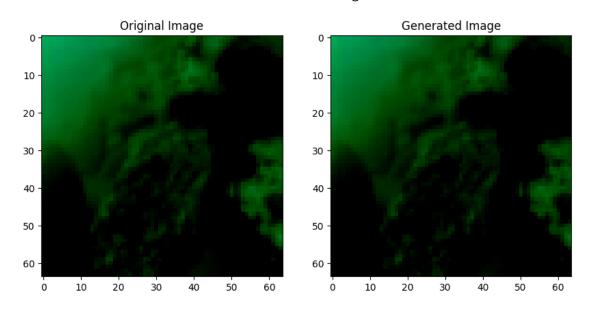


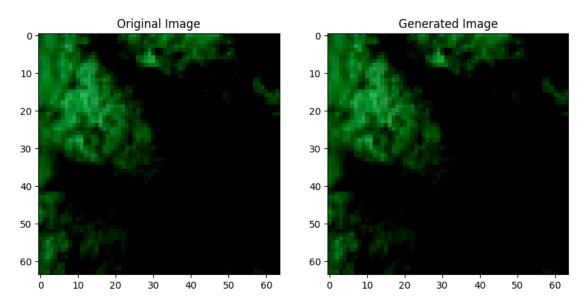


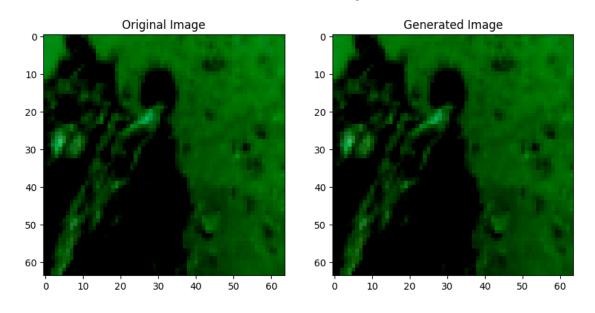


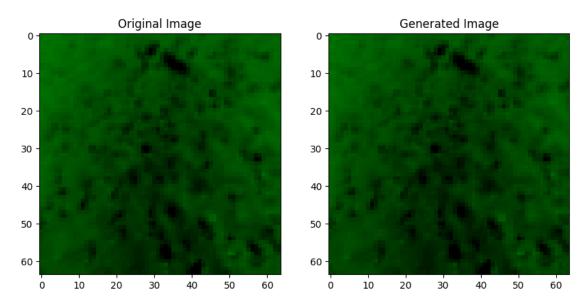


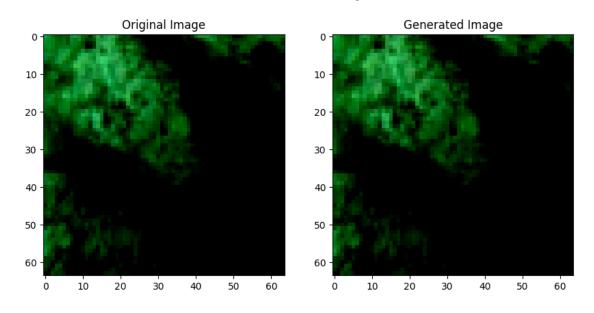


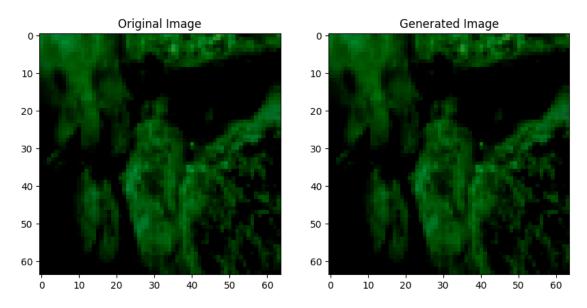


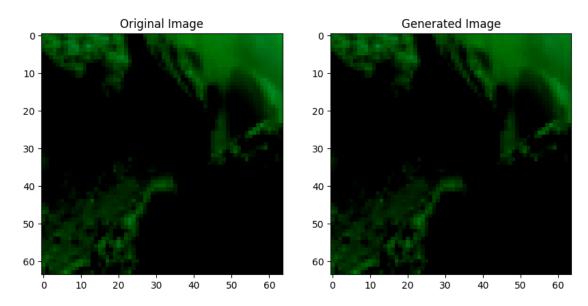












Average PSNR: 35.36

Average Precision: 0.9621 Average Recall: 0.9025 Average Accuracy: 0.9925 Average UCIQE: 0.2514 Average UIQM: 1.1910