Underwater Image Enhancement - Shreyas Lal

Subtask 1: Variational Autoencoders (VAEs)

Import necessary libraries

```
import os
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras import layers, models
from tensorflow.keras.preprocessing.image import load_img, 
img_to_array
import tensorflow as tf
from skimage.metrics import structural_similarity as ssim
```

Set paths

```
train_raw_path = '/kaggle/input/slal-task2-dataset/Train/Raw/'
train_ref_path = '/kaggle/input/slal-task2-dataset/Train/Reference/'
```

Load Images

Function to load and preprocess images

```
def load_images(path, target_size=(480, 640)):
    images = []  # Initialize an empty list to store images
    for file in os.listdir(path):  # Loop through each file in the 
directory
        # Ensure the file is a valid image
        if file.endswith(('.png', '.jpg', '.jpeg')):  # Only load 
image files
            img = load_img(os.path.join(path, file), target_size=(480, 
640)) # Load and resize image
            img = img_to_array(img) / 255.0  # Convert to array and 
normalize pixel values to [0, 1]
            images.append(img)  # Add the preprocessed image to the 
list
    return np.array(images)  # Convert list to numpy array and return
```

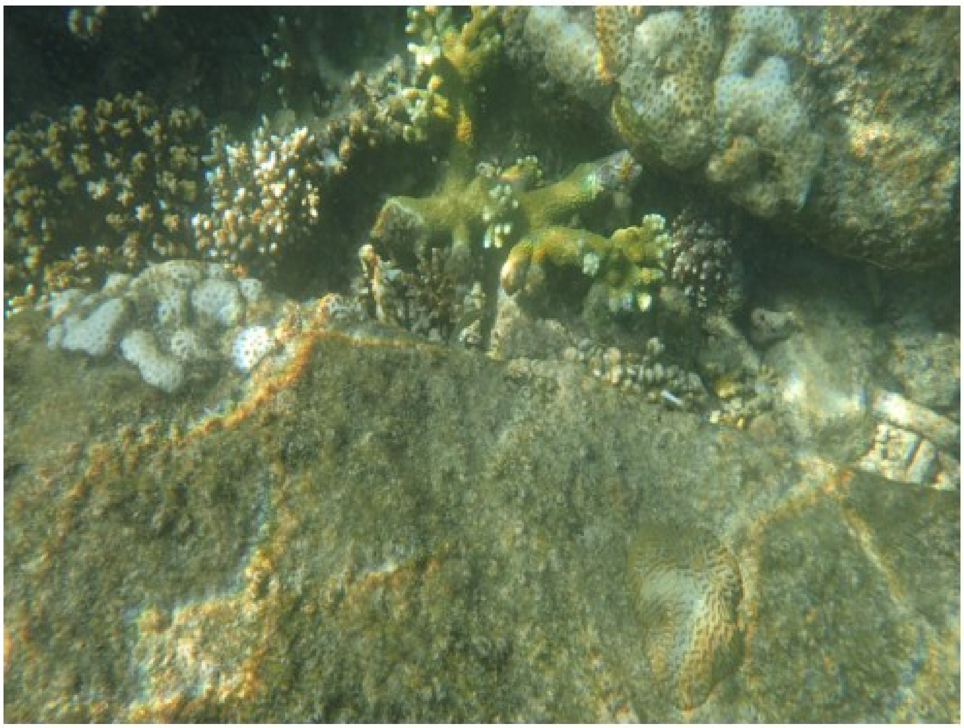
Load training images and reference images

```
train_images = load_images(train_raw_path)
reference_images = load_images(train_ref_path)
```

Visualize a few loaded images

```python
for i in range(min(5, len(train_images))):
    plt.imshow(train_images[i])
    plt.axis('off')
    plt.title(f'Training Image {i+1}')
    plt.show()
```

Training Image 1



Training Image 2

Training Image 3

Training Image 4

Training Image 5

```python
# Define the VAE model
def build_vae():
    inputs = layers.Input(shape=(480, 640, 3))  # Input shape for images

    # Encoder
    x = layers.Conv2D(32, 3, activation='relu', padding='same')(inputs)  # 1st convolutional layer
    x = layers.MaxPooling2D((2, 2))(x)  # Downsample the feature maps

    x = layers.Conv2D(64, 3, activation='relu', padding='same')(x)  # 2nd convolutional layer
    x = layers.MaxPooling2D((2, 2))(x)  # Further downsampling

    x = layers.Conv2D(128, 3, activation='relu', padding='same')(x)  # 3rd convolutional layer
    x = layers.MaxPooling2D((2, 2))(x)  # Further downsampling

    # Latent space
    x = layers.Flatten()(x)  # Flatten the output
    z_mean = layers.Dense(64)(x)  # Mean of the latent space
    z_log_var = layers.Dense(64)(x)  # Log variance of the latent space

    # Sampling layer
    z = layers.Lambda(sampling, output_shape=(64,))([z_mean, z_log_var])  # Sample from the latent space

    # Decoder
    x = layers.Dense(30 * 40 * 128, activation='relu')(z)  # Expand the latent representation
    x = layers.Reshape((30, 40, 128))(x)  # Reshape to a 3D tensor

    # Deconvolutional layers to upsample back to the original image size
    x = layers.Conv2DTranspose(128, 3, activation='relu', padding='same')(x)  # 1st upsampling step
    x = layers.UpSampling2D((2, 2))(x)  # Upsample the feature maps

    x = layers.Conv2DTranspose(64, 3, activation='relu', padding='same')(x)  # 2nd upsampling step
    x = layers.UpSampling2D((2, 2))(x)  # Upsample again

    x = layers.Conv2DTranspose(32, 3, activation='relu', padding='same')(x)  # 3rd upsampling step
    x = layers.UpSampling2D((2, 2))(x)  # Upsample again

    # Final layer to output the reconstructed image
    outputs = layers.Conv2DTranspose(3, 3, activation='sigmoid', padding='same')(x)  # 3 channels for RGB
```

```
    vae = models.Model(inputs, outputs)  # Create the VAE model
    return vae

# Function for sampling from the latent space
def sampling(args):
    z_mean, z_log_var = args  # Get mean and log variance
    batch = tf.shape(z_mean)[0]  # Get the batch size
    dim = tf.shape(z_mean)[1]  # Get the dimension of the latent space
    epsilon = tf.keras.backend.random_normal(shape=(batch, dim))  #
Sample epsilon
    return z_mean + tf.exp(0.5 * z_log_var) * epsilon  # Return the
sampled latent vector

# Load images
train_raw_path = '/kaggle/input/slal-task2-dataset/Train/Raw/'
train_images = load_images(train_raw_path)

# Compile and train the VAE
vae = build_vae()  # Build the VAE model
vae.compile(optimizer='adam', loss='binary_crossentropy')  # Compile
model with Adam optimizer and binary crossentropy loss
vae.fit(train_images, train_images, epochs=50, batch_size=32)  # Train
the VAE

# Function to generate enhanced images from the VAE
def generate_images(model, n=10):
    noise = np.random.normal(size=(n, 64))  # Generate noise in the
latent space size (64)
    generated_images = model.predict(noise)  # Use the VAE model to
generate images from the noise
    return generated_images

# Generate and visualize the enhanced images
generated_images = generate_images(vae, n=5)

# Evaluate and compare original and generated images
def evaluate_images(original, generated):
    mse_scores = []  # Store Mean Squared Error scores
    ssim_scores = []  # Store Structural Similarity Index scores
    for orig, gen in zip(original, generated):
        mse = mean_squared_error(orig.flatten(), gen.flatten())  #
Calculate MSE
        ssim_value = ssim(orig, gen, multichannel=True)  # Calculate
SSIM
        mse_scores.append(mse)  # Append MSE score
        ssim_scores.append(ssim_value)  # Append SSIM score
    return mse_scores, ssim_scores

# Evaluate the first few original images against generated images
```

```
mse_scores, ssim_scores = evaluate_images(train_images[:5],
generated_images)

# Print evaluation results
print("Mean Squared Errors (MSE):", mse_scores)
print("Structural Similarity Indices (SSIM):", ssim_scores)

# Visualize original vs generated images
def visualize_comparison(original, generated):
    n = min(len(original), len(generated))
    plt.figure(figsize=(15, 6))
    for i in range(n):
        plt.subplot(2, n, i + 1)
        plt.imshow(original[i])  # Original image
        plt.axis('off')  # Turn off axis labels
        plt.title("Original")

        plt.subplot(2, n, i + 1 + n)
        plt.imshow(generated[i])  # Generated image
        plt.axis('off')  # Turn off axis labels
        plt.title("Generated")
    plt.show()

# Compare the first few original and generated images
visualize_comparison(train_images[:5], generated_images)
```

```
Epoch 1/50

----------------------------------------------------------------------
-----
ValueError                                Traceback (most recent call
last)
Cell In[12], line 58
     56 vae = build_vae()  # Build the VAE model
     57 vae.compile(optimizer='adam', loss='binary_crossentropy')  #
Compile model with Adam optimizer and binary crossentropy loss
---> 58 vae.fit(train_images, train_images, epochs=50, batch_size=32)
# Train the VAE
     60 # Function to generate enhanced images from the VAE
     61 def generate_images(model, n=10):

File
/opt/conda/lib/python3.10/site-packages/keras/src/utils/traceback_util
s.py:122, in filter_traceback.<locals>.error_handler(*args, **kwargs)
    119     filtered_tb = _process_traceback_frames(e.__traceback__)
    120     # To get the full stack trace, call:
    121     # `keras.config.disable_traceback_filtering()`
--> 122     raise e.with_traceback(filtered_tb) from None
    123 finally:
    124     del filtered_tb
```

```
File
/opt/conda/lib/python3.10/site-packages/keras/src/backend/tensorflow/
nn.py:668, in binary_crossentropy(target, output, from_logits)
    666 for e1, e2 in zip(target.shape, output.shape):
    667     if e1 is not None and e2 is not None and e1 != e2:
--> 668         raise ValueError(
    669             "Arguments `target` and `output` must have the
same shape. "
    670             "Received: "
    671             f"target.shape={target.shape},
output.shape={output.shape}"
    672         )
    674 output, from_logits = _get_logits(
    675     output, from_logits, "Sigmoid", "binary_crossentropy"
    676 )
    678 if from_logits:

ValueError: Arguments `target` and `output` must have the same shape.
Received: target.shape=(None, 480, 640, 3), output.shape=(None, 240,
320, 3)
```

VAE Modelling

```
# Sampling function for the reparameterization trick in VAEs
def sampling(args):
    z_mean, z_log_var = args
    batch = tf.shape(z_mean)[0]
    dim = tf.shape(z_mean)[1]
    epsilon = tf.keras.backend.random_normal(shape=(batch, dim))
    return z_mean + tf.exp(0.5 * z_log_var) * epsilon

# Build the VAE model
def build_vae():
    # Input shape adjusted for 640x480 RGB images
    inputs = layers.Input(shape=(480, 640, 3))

    # Encoder
    x = layers.Conv2D(32, 3, activation='relu', padding='same')
(inputs)
    x = layers.MaxPooling2D()(x)
    x = layers.Conv2D(64, 3, activation='relu', padding='same')(x)
    x = layers.MaxPooling2D()(x)

    # Latent space representation
    x = layers.Flatten()(x)
    x = layers.Dense(128, activation='relu')(x)  # Increased dense
layer for complexity
```

```
    # Mean and log variance for the latent space
    z_mean = layers.Dense(32)(x)
    z_log_var = layers.Dense(32)(x)

    # Sample a point in latent space
    z = layers.Lambda(sampling)([z_mean, z_log_var])

    # Decoder
    x = layers.Dense(120 * 160 * 64, activation='relu')(z)  # Adjust
based on downsampling
    x = layers.Reshape((120, 160, 64))(x)

    x = layers.Conv2DTranspose(64, 3, activation='relu',
padding='same')(x)
    x = layers.UpSampling2D()(x)
    x = layers.Conv2DTranspose(32, 3, activation='relu',
padding='same')(x)
    x = layers.UpSampling2D()(x)

    # Final layer to output the reconstructed image with the same
shape as the input
    outputs = layers.Conv2DTranspose(3, 3, activation='sigmoid',
padding='same')(x)

    # Define the VAE model
    vae = models.Model(inputs, outputs)

    # Encoder and decoder models for optional use
    encoder = models.Model(inputs, z_mean)

    # Decoder input is latent space, then generate the image
    latent_inputs = layers.Input(shape=(32,))
    x = layers.Dense(120 * 160 * 64, activation='relu')(latent_inputs)
    x = layers.Reshape((120, 160, 64))(x)
    x = layers.Conv2DTranspose(64, 3, activation='relu',
padding='same')(x)
    x = layers.UpSampling2D()(x)
    x = layers.Conv2DTranspose(32, 3, activation='relu',
padding='same')(x)
    x = layers.UpSampling2D()(x)
    decoded_output = layers.Conv2DTranspose(3, 3,
activation='sigmoid', padding='same')(x)
    decoder = models.Model(latent_inputs, decoded_output)

    return vae, encoder, decoder

# Compile and train the VAE
vae, encoder, decoder = build_vae()
```

```
vae.compile(optimizer='adam', loss='binary_crossentropy')

# Assuming 'train_images' is your dataset of underwater images
# Normalize train_images to the range [0, 1]
train_images = train_images / 255.0

vae.fit(train_images, train_images, epochs=50, batch_size=32)

# Function to generate images from random latent space vectors
def generate_images(decoder, n=10):
    noise = np.random.normal(size=(n, 32))  # Generate random vectors
in latent space
    generated_images = decoder.predict(noise)  # Generate images using
decoder
    return generated_images

# Generate and visualize the generated images
generated_images = generate_images(decoder)

for i in range(len(generated_images)):
    plt.imshow(generated_images[i])
    plt.axis('off')
    plt.show()

def build_vae():
    # Define the input shape for the encoder; here it's set for
128x128 RGB images
    inputs = layers.Input(shape=(128, 128, 3))

    # Encoder
    #Start with a convolutional layer followed by max pooling
    x = layers.Conv2D(32, 3, activation='relu', padding='same')
(inputs)# 32 filters, kernel size of 3x3
    x = layers.MaxPooling2D()(x) # Downsample the feature maps

    # Another convolutional layer to extract more features
    x = layers.Conv2D(64, 3, activation='relu', padding='same')(x) #
64 filters
    x = layers.MaxPooling2D()(x) # Further downsampling

    # Latent space
    #Flatten the output from the convolutional layers to create a
vector representation
    latent_space = layers.Flatten()(x) # Convert to a 1D vector
    latent_space = layers.Dense(32)(latent_space) # Dense layer for
latent representation

    # Decoder
    # Reconstruct the image from the latent space
    x = layers.Dense(64 * 32 * 32, activation='relu')(latent_space) #
```

```
Dense layer to expand the latent representation
    x = layers.Reshape((32, 32, 64))(x) # Reshape into a 3D tensor
(32x32 feature maps with 64 channels)

    # Deconvolutional layers to upsample back to the original image
size
    x = layers.Conv2DTranspose(64, 3, activation='relu',
padding='same')(x) # First upsampling step
    x = layers.UpSampling2D()(x) # Upsample the feature maps

    x = layers.Conv2DTranspose(32, 3, activation='relu',
padding='same')(x) # Second upsampling step
    x = layers.UpSampling2D()(x) # Unsample again

    # Final layer to output the reconstructed image with same
dimensions as input
    outputs = layers.Conv2DTranspose(3, 3, activation='sigmoid',
padding='same')(x)

    # Create the VAE model combining inputs and outputs
    vae = models.Model(inputs, outputs)
    return vae

# Compile and train the VAE
vae = build_vae() # Build the VAE model
vae.compile(optimizer='adam', loss='binary_crossentropy') # Compile
model with Adam optimizer and binary crossentropy loss
vae.fit(train_images, train_images, epochs=50, batch_size=32) # Train
the VAE, using images as both input and output

# Function to generate enhanced images from the VAE
def generate_images(model, n=10):
    # Create an array of random noise with the same shape as the
images
    noise = np.random.normal(size=(n, 128, 128, 3))  # Sample random
noise
    generated_images = model.predict(noise) # Use the VAE model to
generate images from the noise
    return generated_images

# Generate and visualize images
generated_images = generate_images(vae) # Call the function to
generate a specified number of images
for i in range(len(generated_images)): # Loop through generated images
    plt.imshow(generated_images[i])
    plt.axis('off')
    plt.show()

Epoch 1/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 25s 985ms/step - loss: 0.6609
```

```
Epoch 2/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 931ms/step - loss: 0.6310
Epoch 3/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 42s 968ms/step - loss: 0.6272
Epoch 4/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 952ms/step - loss: 0.6244
Epoch 5/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 959ms/step - loss: 0.6160
Epoch 6/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 935ms/step - loss: 0.6054
Epoch 7/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 935ms/step - loss: 0.5972
Epoch 8/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 949ms/step - loss: 0.5949
Epoch 9/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 932ms/step - loss: 0.5884
Epoch 10/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 970ms/step - loss: 0.5885
Epoch 11/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 22s 1s/step - loss: 0.5834
Epoch 12/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 40s 955ms/step - loss: 0.5843
Epoch 13/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 20s 925ms/step - loss: 0.5786
Epoch 14/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 967ms/step - loss: 0.5787
Epoch 15/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 40s 923ms/step - loss: 0.5820
Epoch 16/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 957ms/step - loss: 0.5718
Epoch 17/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 20s 929ms/step - loss: 0.5743
Epoch 18/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 942ms/step - loss: 0.5757
Epoch 19/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 946ms/step - loss: 0.5732
Epoch 20/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 943ms/step - loss: 0.5741
Epoch 21/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 941ms/step - loss: 0.5743
Epoch 22/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 936ms/step - loss: 0.5770
Epoch 23/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 954ms/step - loss: 0.5741
Epoch 24/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 20s 928ms/step - loss: 0.5635
Epoch 25/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 20s 907ms/step - loss: 0.5668
Epoch 26/50
```

```
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 935ms/step - loss: 0.5685
Epoch 27/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 20s 902ms/step - loss: 0.5660
Epoch 28/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 949ms/step - loss: 0.5707
Epoch 29/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 40s 910ms/step - loss: 0.5612
Epoch 30/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 945ms/step - loss: 0.5674
Epoch 31/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 955ms/step - loss: 0.5678
Epoch 32/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 947ms/step - loss: 0.5663
Epoch 33/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 935ms/step - loss: 0.5666
Epoch 34/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 921ms/step - loss: 0.5629
Epoch 35/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 946ms/step - loss: 0.5572
Epoch 36/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 955ms/step - loss: 0.5650
Epoch 37/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 949ms/step - loss: 0.5592
Epoch 38/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 941ms/step - loss: 0.5591
Epoch 39/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 945ms/step - loss: 0.5600
Epoch 40/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 20s 923ms/step - loss: 0.5650
Epoch 41/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 962ms/step - loss: 0.5632
Epoch 42/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 952ms/step - loss: 0.5619
Epoch 43/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 20s 915ms/step - loss: 0.5648
Epoch 44/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 958ms/step - loss: 0.5619
Epoch 45/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 936ms/step - loss: 0.5627
Epoch 46/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 22s 996ms/step - loss: 0.5614
Epoch 47/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 41s 971ms/step - loss: 0.5632
Epoch 48/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 22s 1s/step - loss: 0.5602
Epoch 49/50
22/22 ━━━━━━━━━━━━━━━━━━━━ 21s 937ms/step - loss: 0.5589
Epoch 50/50
```

```
22/22 ━━━━━━━━━━━━━━━━━━━━ 42s 963ms/step - loss: 0.5597
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 313ms/step
```