```python
import zipfile
import os

# Path to uploaded ZIP file
uploaded_zip_path = '/content/Coil.zip'
extraction_path = '/content/'

# Extract the ZIP file
with zipfile.ZipFile(uploaded_zip_path, 'r') as zip_ref:
    zip_ref.extractall(extraction_path)

# Check extracted contents
extracted_files = os.listdir(extraction_path)
print(f"Extracted {len(extracted_files)} files.")
```

```
Extracted 6 files.
```

1. Dataset:

- Use the Columbia University Object Image Library (COIL) dataset.
- Split the dataset into training (80%) and testing (20%) sets.

```python
import os
import numpy as np
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing.image import load_img,
img_to_array

# Path to COIL dataset
data_path = '/content/coil-20-proc'
image_size = (128, 128)  # Resize images for uniformity
images = []
labels = []

# Load images and resize
for file in os.listdir(data_path):
    if file.endswith('.png'):  # Assuming COIL images are PNG
        img = load_img(os.path.join(data_path, file),
target_size=image_size)
        img_array = img_to_array(img) / 255.0  # Normalize pixel
values to [0, 1]
        images.append(img_array)

images = np.array(images)
print(f"Dataset shape: {images.shape}")

# Split dataset into training (80%) and testing (20%)
X_train, X_test = train_test_split(images, test_size=0.2,
random_state=42)
```

```
print(f"Training set shape: {X_train.shape}, Testing set shape:
{X_test.shape}")
```

```
Dataset shape: (1440, 128, 128, 3)
Training set shape: (1152, 128, 128, 3), Testing set shape: (288, 128,
128, 3)
```

1. Model Development:

- Construct a CNN Autoencoder with:
  - Encoder: Use convolutional layers with ReLU activation to reduce the input image to a lower-dimensional latent representation.
  - Decoder: Use transpose convolutional layers to reconstruct the image from the latent space.

```
import tensorflow as tf
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Conv2D, ReLU,
Conv2DTranspose, Flatten, Dense, Reshape

# Encoder
def build_encoder(input_shape):
    inputs = Input(shape=input_shape)
    x = Conv2D(32, (3, 3), activation='relu', padding='same')(inputs)
    x = Conv2D(64, (3, 3), activation='relu', padding='same',
strides=(2, 2))(x)
    x = Conv2D(128, (3, 3), activation='relu', padding='same',
strides=(2, 2))(x)
    latent = Flatten()(x)
    latent = Dense(128, activation='relu')(latent)
    return Model(inputs, latent, name="Encoder")

# Decoder
def build_decoder(latent_dim, original_shape):
    latent_inputs = Input(shape=(latent_dim,))
    x = Dense(np.prod(original_shape), activation='relu')
(latent_inputs)
    x = Reshape(original_shape)(x)
    x = Conv2DTranspose(128, (3, 3), activation='relu',
padding='same', strides=(2, 2))(x)
    x = Conv2DTranspose(64, (3, 3), activation='relu', padding='same',
strides=(2, 2))(x)
    outputs = Conv2DTranspose(3, (3, 3), activation='sigmoid',
padding='same')(x)
    return Model(latent_inputs, outputs, name="Decoder")

# Autoencoder
input_shape = X_train.shape[1:]  # Image dimensions
encoder = build_encoder(input_shape)
decoder = build_decoder(latent_dim=128, original_shape=(32, 32, 128))
```

```
autoencoder = Model(encoder.input, decoder(encoder.output),
name="Autoencoder")
autoencoder.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0
.001), loss='mse')

autoencoder.summary()

Model: "Autoencoder"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━┓
━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                          ┃ Output Shape               ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━┩
━━━━━━━━━━━━━━━━━┩
│ input_layer_2 (InputLayer)            │ (None, 128, 128, 3)        │
0 │
├───────────────────────────────────────┼────────────────────────────┤
─────────────────┤
│ conv2d_3 (Conv2D)                     │ (None, 128, 128, 32)       │
896 │
├───────────────────────────────────────┼────────────────────────────┤
─────────────────┤
│ conv2d_4 (Conv2D)                     │ (None, 64, 64, 64)         │
18,496 │
├───────────────────────────────────────┼────────────────────────────┤
─────────────────┤
│ conv2d_5 (Conv2D)                     │ (None, 32, 32, 128)        │
73,856 │
├───────────────────────────────────────┼────────────────────────────┤
─────────────────┤
│ flatten_1 (Flatten)                   │ (None, 131072)             │
0 │
├───────────────────────────────────────┼────────────────────────────┤
─────────────────┤
│ dense_2 (Dense)                       │ (None, 128)                │
16,777,344 │
├───────────────────────────────────────┼────────────────────────────┤
─────────────────┤
│ Decoder (Functional)                  │ (None, 128, 128, 3)        │
17,131,395 │
└───────────────────────────────────────┴────────────────────────────┘
─────────────────┘

 Total params: 34,001,987 (129.71 MB)

 Trainable params: 34,001,987 (129.71 MB)

 Non-trainable params: 0 (0.00 B)
```

1. Training:

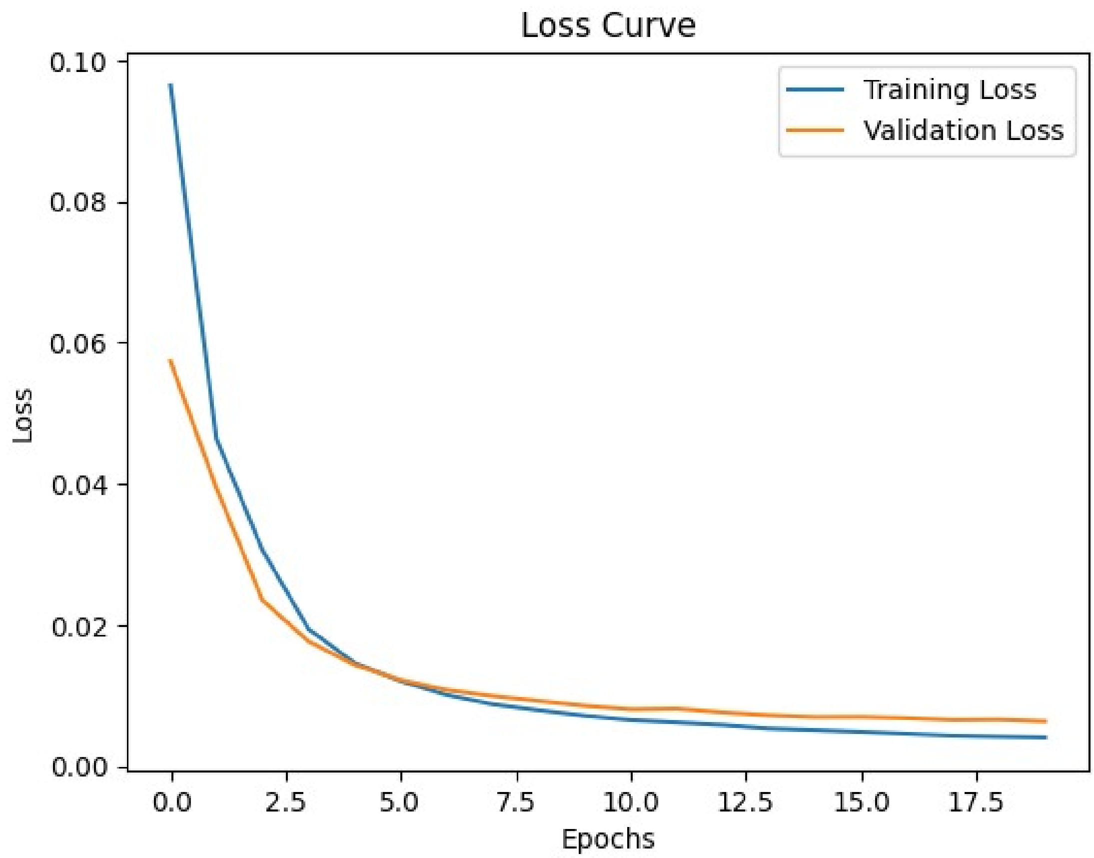
- Use the Mean Squared Error (MSE) loss function.
- Use Adam optimizer with a learning rate of 0.001.
- Train the model for 20 epochs with a suitable batch size.

```
history = autoencoder.fit(X_train, X_train,
                          validation_data=(X_test, X_test),
                          epochs=20,
                          batch_size=32,
                          shuffle=True)

# Plot the training loss curve
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Loss Curve')
plt.show()

Epoch 1/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 7s 93ms/step - loss: 0.1225 - val_loss:
0.0573
Epoch 2/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 70ms/step - loss: 0.0506 - val_loss:
0.0393
Epoch 3/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 73ms/step - loss: 0.0341 - val_loss:
0.0235
Epoch 4/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 76ms/step - loss: 0.0203 - val_loss:
0.0176
Epoch 5/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 5s 72ms/step - loss: 0.0150 - val_loss:
0.0143
Epoch 6/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 5s 72ms/step - loss: 0.0120 - val_loss:
0.0122
Epoch 7/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 5s 73ms/step - loss: 0.0101 - val_loss:
0.0108
Epoch 8/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 75ms/step - loss: 0.0087 - val_loss:
0.0099
Epoch 9/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 75ms/step - loss: 0.0079 - val_loss:
0.0092
Epoch 10/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 73ms/step - loss: 0.0070 - val_loss:
0.0085
Epoch 11/20
```

```
36/36 ━━━━━━━━━━━━━━━━━━━━ 5s 73ms/step - loss: 0.0064 - val_loss:
0.0080
Epoch 12/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 76ms/step - loss: 0.0062 - val_loss:
0.0081
Epoch 13/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 5s 78ms/step - loss: 0.0060 - val_loss:
0.0076
Epoch 14/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 5s 73ms/step - loss: 0.0054 - val_loss:
0.0072
Epoch 15/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 73ms/step - loss: 0.0050 - val_loss:
0.0069
Epoch 16/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 5s 77ms/step - loss: 0.0047 - val_loss:
0.0069
Epoch 17/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 5s 77ms/step - loss: 0.0045 - val_loss:
0.0068
Epoch 18/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 5s 74ms/step - loss: 0.0043 - val_loss:
0.0065
Epoch 19/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 5s 78ms/step - loss: 0.0041 - val_loss:
0.0066
Epoch 20/20
36/36 ━━━━━━━━━━━━━━━━━━━━ 3s 74ms/step - loss: 0.0040 - val_loss:
0.0063
```



1. Evaluation:

- Evaluate the model's performance using the testing set.
- Visualize the reconstructed images and compare them to the original images.
- Calculate and report the MSE on the test set.

```
# Evaluate MSE on test set
test_loss = autoencoder.evaluate(X_test, X_test, batch_size=32)
print(f"Test MSE: {test_loss}")

# Visualize original vs reconstructed images
n_examples = 5
reconstructed_images = autoencoder.predict(X_test[:n_examples])

plt.figure(figsize=(10, 5))
for i in range(n_examples):
    # Original image
    plt.subplot(2, n_examples, i + 1)
    plt.imshow(X_test[i])
    plt.title("Original")
    plt.axis('off')

    # Reconstructed image
    plt.subplot(2, n_examples, i + n_examples + 1)
```

```
    plt.imshow(reconstructed_images[i])
    plt.title("Reconstructed")
    plt.axis('off')
plt.show()

3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - loss: 0.0192
Test MSE: 0.018903402611613274
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step
```