

DeepLearning Project

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Course - Deep Learning and Reinforcement Learning

Main Objective:

1. Use of CNN to classify grapevine leaves
2. Use of Variational Autoencoder for generating synthetic image dataset

Dataset Used - Grapevine Leaves Image Dataset

Pistachio is a shelled fruit from the anacardiaceae family. The homeland of pistachio is the Middle East. The Kirmizi pistachios and Siirt pistachios are the major types grown and exported in Turkey. Since the prices, tastes, and nutritional values of these types differs, the type of pistachio becomes important when it comes to trade. This study aims to identify these two types of pistachios, which are frequently grown in Turkey, by classifying them via convolutional neural networks. Within the scope of the study, images of Kirmizi and Siirt pistachio types were obtained through the computer vision system. The pre-trained dataset includes a total of 2148 images, 1232 of Kirmizi type and 916 of Siirt type. Three different convolutional neural network models were used to classify these images. Models were trained by using the transfer learning method, with AlexNet and the pre-trained models VGG16 and VGG19. The dataset is divided as 80% training and 20% test. As a result of the performed classifications, the success rates obtained from the AlexNet, VGG16, and VGG19 models are 94.42%, 98.84%, and 98.14%, respectively. Models' performances were evaluated through sensitivity, specificity, precision, and F-1 score metrics. In addition, ROC curves and AUC values were used in the performance evaluation. The highest classification success was achieved with the VGG16 model. The obtained results reveal that these methods can be used successfully in the determination of pistachio types.

1. Classification of five classes of grapevine leaves by CNN Model
2. Use of Variational AutoEncoder to generate synthetic Images

Dataset:

1. Contains 2248 images
2. belonging to 2 categories
Classes are ---
3. Kirmizi_Pistachio = 0,
4. Siirt_Pistachio = 1,

```
In [1]: import os
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from keras.layers import Dense, Conv2D, Conv2DTranspose, Flatten, RandomRotation
from keras.metrics import Accuracy
from keras.models import Model, Sequential
```

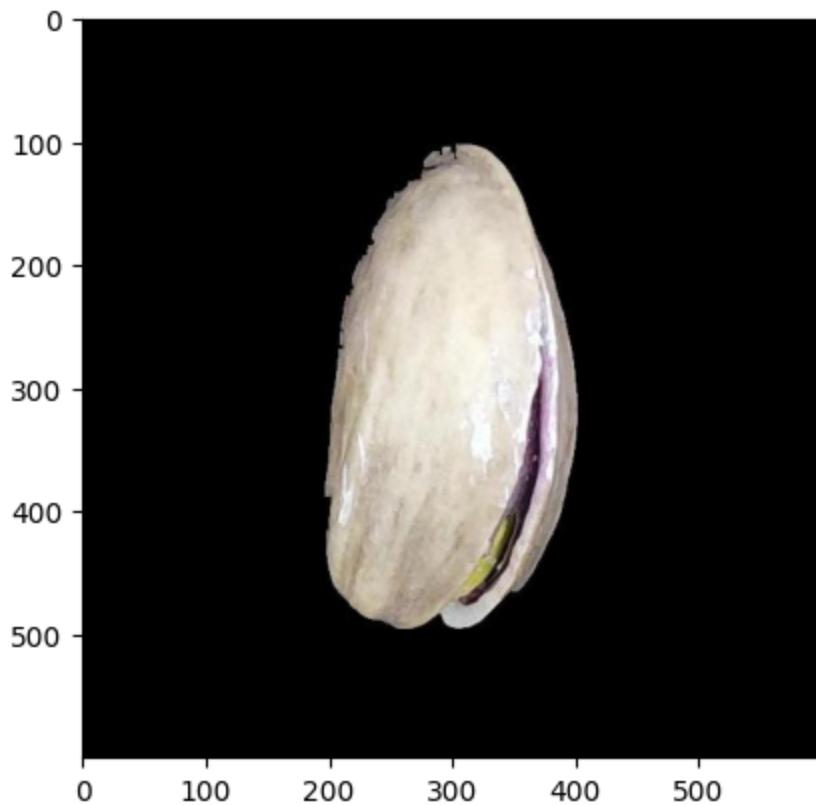
```
In [103... !curl https://www.muratkoklu.com/datasets/Pistachio_Image_Dataset.zip -o file.zip
% Total    % Received % Xferd  Average Speed   Time     Time     Time  Current
                                         Dload  Upload   Total  Spent   Left  Speed
d 100 26.5M  100 26.5M    0      0  7226k      0  0:00:03  0:00:03  --:--:-- 722
6k
```

```
In [ ]: !unzip file.zip
```

```
In [105... !ls
file.zip                  Pistachio_Image_Dataset  sample_data
Grapevine_Leaves_Image_Dataset  Pumpkin_Seeds_Dataset
```

```
In [116... from PIL import Image
i = Image.open('Pistachio_Image_Dataset/Pistachio_Image_Dataset/Kirmizi_Pistachio')
plt.imshow(i)
print(np.array(i).shape)
```

(600, 600, 3)



DATA ENGINEERING

KERAS IMAGE DATA GENERATOR IS USED TO MAKE THE DATASET

IMAGES ARE SCALED BETWEEN 0 AND 1

IMAGES ARE RESHAPE FROM (600,600,3) TO (256,256,1) TO TRAIN THE MODEL FASTER

IMAGES ARE CONVERTED FROM RGB TO GRayscale FOR REDUCING THE COMPUTATIONAL COST

IMAGES ARE SPLIT IN TRAINING SET 80% AND VALIDATION SET 20%

```
In [117]: datagen = ImageDataGenerator(  
    rescale=1./255,  
    validation_split=0.2,  
)  
img_size = (256,256)  
batch_size = 32  
  
train_generator = datagen.flow_from_directory(  
    'Pistachio_Image_Dataset/Pistachio_Image_Dataset',  
    target_size=img_size,  
    batch_size=batch_size,  
    class_mode='categorical',  
    subset='training',
```

```

        color_mode='grayscale'
    )

validation_generator = datagen.flow_from_directory(
    'Pistachio_Image_Dataset/Pistachio_Image_Dataset',
    target_size=img_size,
    batch_size=batch_size,
    class_mode='categorical',
    subset='validation',
    color_mode='grayscale'
)

```

Found 1719 images belonging to 2 classes.

Found 429 images belonging to 2 classes.

In [149... path = 'Pistachio_Image_Dataset/Pistachio_Image_Dataset'
image_batch, label_batch = next(iter(train_generator))]

In [118... REVERSE_LOOKUP = {j:i for i,j in train_generator.class_indices.items()}

In [132... REVERSE_LOOKUP

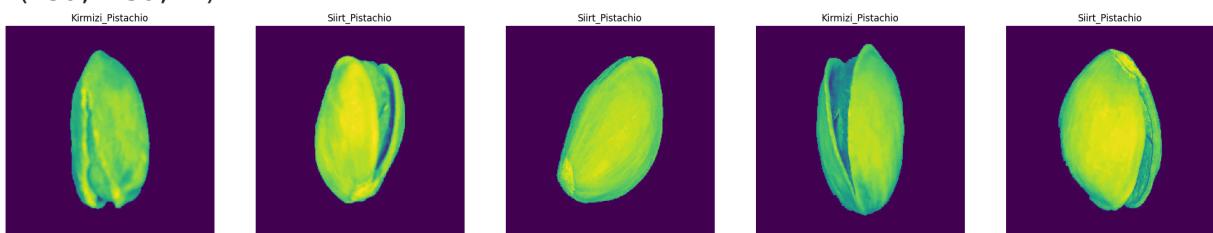
Out[132... {0: 'Kirmizi_Pistachio', 1: 'Siirt_Pistachio'}

In [127... def plot_images(datagen):
 images, labels = next(datagen)
 fig = plt.figure(figsize=(28, 28))
 for i in range(5):
 ax = fig.add_subplot(1,5, i+1)
 ax.axis('off')
 print(images[i].shape)
 plt.title(REVERSE_LOOKUP[np.argmax(labels[i])])
 ax.imshow(images[i])

 plt.show()

In [128... plot_images(train_generator)

(256, 256, 1)
(256, 256, 1)
(256, 256, 1)
(256, 256, 1)
(256, 256, 1)



MODEL TRAINED

LAYERS USED ARE - CONV2D, AVERAGEPOOLING2D , BATCHNORMALIZATION, FLATTEN

MODEL LAYOUT:

CONV2D --> AVERAGEPOOLING2D --> BATCHNORMALIZATION --> CONV2D -->
 AVERAGEPOOLING2D --> BATCHNORMALIZATION --> FLATTEN --> DENSE -->
 BATCHNORMALIZATION --> DENSE --> BATCHNORMALIZATION --> DENSE

(5,5) KERNEL SIZE IS USED IN CONV2D AND AVERAGEPOOLING2D

ACTIVATION USED IS RELU IS INTERMEDIATE LAYERS AND SOFTMAX ON OUTPUT LAYER

LOSS FUNCTION USED IS CATEGORICAL CROSS ENTROPY

OPTIMIZER USED IS ADAM

REACHED ACCURACY OF 88.6% ON VALIDATION AND 93.4% TRAIN SET IN 15 EPOCHS

```
In [129...]: from keras.layers import AveragePooling2D, BatchNormalization

model = Sequential()

# Block 1
model.add(Conv2D(filters=64, kernel_size=(5,5), padding='same', input_shape=)
model.add(AveragePooling2D(pool_size=(5,5)))
model.add(BatchNormalization())

model.add(Conv2D(filters=64, kernel_size=(5,5), padding='same'))
model.add(AveragePooling2D(pool_size=(5,5)))
model.add(BatchNormalization())

model.add(Flatten())

#Block 5
model.add(Dense(256, activation='relu'))
model.add(BatchNormalization())

model.add(Dense(128, activation='relu'))
model.add(BatchNormalization())

model.add(Dense(2, activation='softmax'))

/usr/local/lib/python3.12/dist-packages/keras/src/layers/convolutional/base_
conv.py:113: UserWarning: Do not pass an `input_shape`/`input_dim` argument
to a layer. When using Sequential models, prefer using an `Input(shape)` obj
ect as the first layer in the model instead.
    super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
In [130...]: from keras.losses import CategoricalCrossentropy
model.compile(loss=CategoricalCrossentropy(), optimizer='adam', metrics=['ac...'])

In [133...]: model.fit(train_generator, epochs=15, validation_data=validation_generator)

Epoch 1/15
54/54 0s 82ms/step - accuracy: 0.9335 - loss: 0.1848
/usr/local/lib/python3.12/dist-packages/keras/src/trainers/data_adapters/py_
dataset_adapter.py:121: UserWarning: Your `PyDataset` class should call `sup_
er().__init__(**kwargs)` in its constructor. `**kwargs` can include `workers`_
, `use_multiprocessing`, `max_queue_size`. Do not pass these arguments to `_
fit()`, as they will be ignored.
    self._warn_if_super_not_called()
```

54/54 10s 186ms/step - accuracy: 0.9333 - loss: 0.1851
- val_accuracy: 0.8275 - val_loss: 0.4550
Epoch 2/15
54/54 5s 88ms/step - accuracy: 0.9195 - loss: 0.2100 -
val_accuracy: 0.7459 - val_loss: 0.9682
Epoch 3/15
54/54 6s 115ms/step - accuracy: 0.9116 - loss: 0.2043 -
val_accuracy: 0.5734 - val_loss: 28.7502
Epoch 4/15
54/54 5s 89ms/step - accuracy: 0.9175 - loss: 0.2218 -
val_accuracy: 0.7366 - val_loss: 0.9521
Epoch 5/15
54/54 5s 93ms/step - accuracy: 0.8907 - loss: 0.2581 -
val_accuracy: 0.8741 - val_loss: 0.3585
Epoch 6/15
54/54 5s 96ms/step - accuracy: 0.9261 - loss: 0.1859 -
val_accuracy: 0.7506 - val_loss: 0.6940
Epoch 7/15
54/54 5s 88ms/step - accuracy: 0.9206 - loss: 0.1882 -
val_accuracy: 0.7716 - val_loss: 0.5861
Epoch 8/15
54/54 5s 100ms/step - accuracy: 0.9360 - loss: 0.1671 -
val_accuracy: 0.8322 - val_loss: 0.4052
Epoch 9/15
54/54 5s 92ms/step - accuracy: 0.9216 - loss: 0.1804 -
val_accuracy: 0.8974 - val_loss: 0.2883
Epoch 10/15
54/54 5s 99ms/step - accuracy: 0.9373 - loss: 0.1750 -
val_accuracy: 0.7576 - val_loss: 0.6701
Epoch 11/15
54/54 12s 138ms/step - accuracy: 0.9105 - loss: 0.2043
- val_accuracy: 0.7599 - val_loss: 0.6680
Epoch 12/15
54/54 8s 88ms/step - accuracy: 0.9278 - loss: 0.1770 -
val_accuracy: 0.8462 - val_loss: 0.3866
Epoch 13/15
54/54 6s 104ms/step - accuracy: 0.9281 - loss: 0.1705 -
val_accuracy: 0.7925 - val_loss: 0.5723
Epoch 14/15
54/54 5s 88ms/step - accuracy: 0.9452 - loss: 0.1307 -
val_accuracy: 0.8858 - val_loss: 0.2856
Epoch 15/15
54/54 6s 103ms/step - accuracy: 0.9344 - loss: 0.1437 -
val_accuracy: 0.8858 - val_loss: 0.2782

Out[133]: <keras.src.callbacks.history.History at 0x7af65bdbba5d0>

FURTHER IMPROVEMENT

MORE LAYERS CAN IMPROVE THE ACCURACY AND WE CAN INCOMPORATE DATA AUGMENTATION LIKE RANDOM CROP .

RANDOMFLIP , RANDOMZOOM, RANDOMROTATION TO ACHIEVE BETTER ACCURACY AND AVOID OVERFITTING

In [134...]

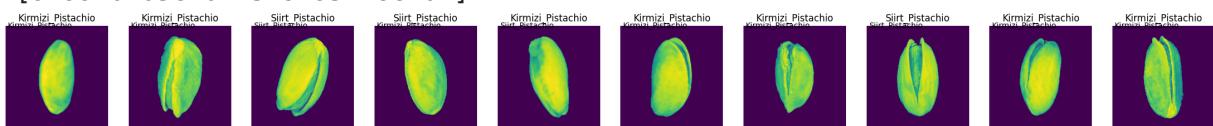
```
def testing(train):
    img, label = next(train)
    pred = model.predict(img)
    fig = plt.figure(figsize=(28,28))
    for i in range(10):
        ax = fig.add_subplot(1, 10, i+1)
        ax.imshow(img[i])
        plt.title(REVERSE_LOOKUP[np.argmax(pred[i])])
        print(pred[i])
        plt.annotate(REVERSE_LOOKUP[np.argmax(label[i])], xy=(0,0), xytext=(0,0))
        ax.axis('off')
    plt.show()
```

In [135...]

```
testing(train_generator)
```

1/1 ━━━━━━ 1s 536ms/step

```
[0.99743605 0.00256389]
[0.8266258  0.17337416]
[0.01446284 0.9855371 ]
[0.25191692 0.7480831 ]
[0.9691049  0.03089514]
[0.9918588  0.00814123]
[0.987604   0.01239591]
[0.4233709  0.57662904]
[0.95772684 0.04227316]
[0.9940705e-01 5.9295748e-04]
```

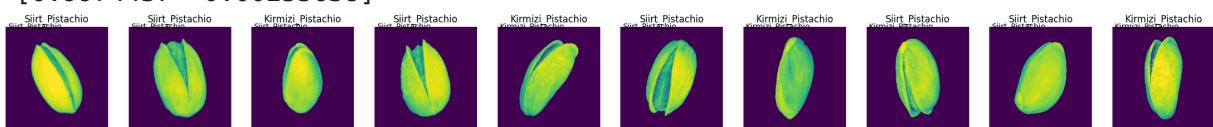


In [136...]

```
testing(validation_generator)
```

1/1 ━━━━━━ 0s 59ms/step

```
[0.00592174 0.9940782 ]
[0.15623409 0.8437659 ]
[0.7904934  0.20950657]
[0.01745241 0.9825476 ]
[0.9999976e-01 2.5469595e-07]
[0.00753659 0.99246335]
[0.999404e-01 5.960925e-05]
[0.02390796 0.97609204]
[0.04975304 0.95024693]
[0.9974437  0.00255638]
```



PART 2: VARIATIONAL AUTOENCODER

DATASET USED - SAME AS PART 1

MODEL USED: (ENCODER AND DECODER MODEL)
VARIATIONAL AUTOENCODER DECOMPOSE THE DATA TO DISTRIBUTION THROUGH ENCODER AND DECODER TRY TO RECREATE INPUT

LAYERS USED: CONV2D, DENSE, FLATTEN, CONV2DTRANSPOSE, DROPOUT, RESHAPE

LOSS FUNCTION IS CUSTOM CREATED AS KL_LOSS AND RECREATION LOSS

OUTPUT OF ENCODER $z = z_mean + \exp(0.5 * z_log_var) * \epsilon$

In [158...]

```
import os
os.environ["KERAS_BACKEND"] = "tensorflow"

import numpy as np
import tensorflow as tf
import keras
from keras import layers
import matplotlib.pyplot as plt

# =====
# 1. The Sampling Layer (Reparameterization)
# =====
class Sampling(layers.Layer):
    """
    Uses (z_mean, z_log_var) to sample z, the vector encoding a digit.
    z = z_mean + exp(0.5 * z_log_var) * epsilon
    """
    def call(self, inputs):
        z_mean, z_log_var = inputs
        batch = tf.shape(z_mean)[0]
        dim = tf.shape(z_mean)[1]

        # Epsilon is random noise from a standard normal distribution
        epsilon = tf.keras.backend.random_normal(shape=(batch, dim))

        # The reparameterization trick
        z = z_mean + tf.exp(0.5 * z_log_var) * epsilon
        return z
```

```

        return z_mean + tf.exp(0.5 * z_log_var) * epsilon

# =====
# 2. Define the Encoder
# =====
latent_dim = 2 # 2D latent space allows us to visualize the manifold later

encoder_inputs = keras.Input(shape=(256, 256, 1))

# Convolutional downsampling
x = layers.Conv2D(32, 3, activation="relu", strides=1, padding="same")(encoder_inputs)
x = layers.Conv2D(64, 3, activation="relu", strides=1, padding="same")(x)
x = layers.Flatten()(x)
x = layers.Dense(16, activation="relu")(x)
x = layers.Dropout(0.4)(x)

# Output two separate vectors: Mean and Log Variance
z_mean = layers.Dense(latent_dim, name="z_mean")(x)
z_log_var = layers.Dense(latent_dim, name="z_log_var")(x)

# Sample the latent vector z
z = Sampling()([z_mean, z_log_var])

encoder = keras.Model(encoder_inputs, [z_mean, z_log_var, z], name="encoder")
encoder.summary()

# =====
# 3. Define the Decoder
# =====
latent_inputs = keras.Input(shape=(latent_dim,))

# Upsampling back to image dimensions
x = layers.Dense(64* 64 * 64, activation="relu")(latent_inputs)
x = layers.Dropout(0.4)(x)
x = layers.Reshape((64, 64, 64))(x)
x = layers.Conv2DTranspose(64, 3, activation="relu", strides=2, padding="same")(x)
x = layers.Conv2DTranspose(32, 3, activation="relu", strides=2, padding="same")(x)

# Sigmoid activation because MNIST pixels are normalized to [0, 1]
decoder_outputs = layers.Conv2DTranspose(1, 3, activation="sigmoid", padding="same")(x)

decoder = keras.Model(latent_inputs, decoder_outputs, name="decoder")
decoder.summary()

# =====
# 4. The VAE Model (Custom Train Step)
# =====
class VAE(keras.Model):
    def __init__(self, encoder, decoder, **kwargs):
        super().__init__(**kwargs)
        self.encoder = encoder
        self.decoder = decoder
        self.total_loss_tracker = keras.metrics.Mean(name="total_loss")
        self.reconstruction_loss_tracker = keras.metrics.Mean(name="reconstruction_loss")
        self.kl_loss_tracker = keras.metrics.Mean(name="kl_loss")

```

```

@property
def metrics(self):
    return [
        self.total_loss_tracker,
        self.reconstruction_loss_tracker,
        self.kl_loss_tracker,
    ]

def train_step(self, data):
    with tf.GradientTape() as tape:
        z_mean, z_log_var, z = self.encoder(data)
        reconstruction = self.decoder(z)

        # 1. Reconstruction Loss (Binary Crossentropy)
        reconstruction_loss = tf.reduce_mean(
            tf.reduce_sum(
                keras.losses.binary_crossentropy(data, reconstruction),
            )
        )

        # 2. KL Divergence Loss
        #  $D_{KL} = -0.5 * \sum(1 + \log(\sigma^2) - \mu^2 - \sigma^2)$ 
        kl_loss = -0.5 * (1 + z_log_var - tf.square(z_mean) - tf.exp(z_l))
        kl_loss = tf.reduce_mean(tf.reduce_sum(kl_loss, axis=1))

        total_loss = reconstruction_loss + kl_loss

        grads = tape.gradient(total_loss, self.trainable_weights)
        self.optimizer.apply_gradients(zip(grads, self.trainable_weights))

        self.total_loss_tracker.update_state(total_loss)
        self.reconstruction_loss_tracker.update_state(reconstruction_loss)
        self.kl_loss_tracker.update_state(kl_loss)

    return {
        "loss": self.total_loss_tracker.result(),
        "reconstruction_loss": self.reconstruction_loss_tracker.result(),
        "kl_loss": self.kl_loss_tracker.result(),
    }

# =====
# 5. Train on MNIST
# =====
# (x_train, _), (x_test, _) = keras.datasets.mnist.load_data()

# Normalize and reshape
# mnist_digits = np.concatenate([x_train, x_test], axis=0)
# mnist_digits = np.expand_dims(mnist_digits, -1).astype("float32") / 255

vae = VAE(encoder, decoder)
vae.compile(optimizer=keras.optimizers.Adam())

print("Starting training...")
vae.fit(image_batch, epochs=400, batch_size=128)

# =====

```

```
# 6. Visualize the Latent Space
# =====
def plot_latent_space(vae, n=2, figsize=15):
    # display a n*n 2D manifold of digits
    digit_size = 256
    scale = 1.0
    figure = np.zeros((digit_size * n, digit_size * n))

    # Linearly spaced coordinates on the unit square were transformed
    # through the inverse CDF (ppf) of the Gaussian
    grid_x = np.linspace(-scale, scale, n)
    grid_y = np.linspace(-scale, scale, n)[::-1]

    for i, yi in enumerate(grid_y):
        for j, xi in enumerate(grid_x):
            z_sample = np.array([[xi, yi]])
            x_decoded = vae.decoder.predict(z_sample, verbose=0)
            digit = x_decoded[0].reshape(digit_size, digit_size)
            figure[
                i * digit_size : (i + 1) * digit_size,
                j * digit_size : (j + 1) * digit_size,
            ] = digit

    plt.figure(figsize=(figsize, figsize))
    start_range = digit_size // 2
    end_range = n * digit_size + start_range
    pixel_range = np.arange(start_range, end_range, digit_size)
    sample_range_x = np.round(grid_x, 1)
    sample_range_y = np.round(grid_y, 1)
    plt.xticks(pixel_range, sample_range_x)
    plt.yticks(pixel_range, sample_range_y)
    plt.xlabel("z[0]")
    plt.ylabel("z[1]")
    plt.imshow(figure, cmap="Greys_r")
    plt.show()

print("Plotting latent space...")
plot_latent_space(vae)
```

Model: "encoder"

Layer (type)	Output Shape	Param #	Connected to
input_layer_46 (InputLayer)	(None, 256, 256, 1)	0	-
conv2d_60 (Conv2D)	(None, 256, 256, 32)	320	input_layer_4
conv2d_61 (Conv2D)	(None, 256, 256, 64)	18,496	conv2d_60[0][0]
flatten_30 (Flatten)	(None, 4194304)	0	conv2d_61[0][0]
dense_82 (Dense)	(None, 16)	67,108,880	flatten_30[0]
dropout_2 (Dropout)	(None, 16)	0	dense_82[0][0]
z_mean (Dense)	(None, 2)	34	dropout_2[0][0]
z_log_var (Dense)	(None, 2)	34	dropout_2[0][0]
sampling_12 (Sampling)	(None, 2)	0	z_mean[0][0], z_log_var[0][0]

◀ ▶ Total params: 67,127,764 (256.07 MB)

Trainable params: 67,127,764 (256.07 MB)

Non-trainable params: 0 (0.00 B)

Model: "decoder"

Layer (type)	Output Shape	Par
input_layer_47 (InputLayer)	(None, 2)	
dense_83 (Dense)	(None, 262144)	786
dropout_3 (Dropout)	(None, 262144)	
reshape_16 (Reshape)	(None, 64, 64, 64)	
conv2d_transpose_44 (Conv2DTranspose)	(None, 128, 128, 64)	36
conv2d_transpose_45 (Conv2DTranspose)	(None, 256, 256, 32)	18
conv2d_transpose_46 (Conv2DTranspose)	(None, 256, 256, 1)	

◀ ▶ Total params: 842,113 (3.21 MB)

Trainable params: 842,113 (3.21 MB)

Non-trainable params: 0 (0.00 B)

Starting training...

Epoch 1/400

1/1 **17s** 17s/step - kl_loss: 0.0011 - loss: 45437.7734 - reconstruction_loss: 45437.7734

Epoch 2/400

1/1 **0s** 203ms/step - kl_loss: 3687.8333 - loss: 49157.3438 - reconstruction_loss: 45469.5117

Epoch 3/400

1/1 **0s** 203ms/step - kl_loss: 129.1369 - loss: 45402.8867 - reconstruction_loss: 45273.7500

Epoch 4/400

1/1 **0s** 202ms/step - kl_loss: 295.8069 - loss: 45428.6289 - reconstruction_loss: 45132.8203

Epoch 5/400

1/1 **0s** 203ms/step - kl_loss: 258.4108 - loss: 45226.6133 - reconstruction_loss: 44968.2031

Epoch 6/400

1/1 **0s** 202ms/step - kl_loss: 193.8894 - loss: 44965.1172 - reconstruction_loss: 44771.2266

Epoch 7/400

1/1 **0s** 200ms/step - kl_loss: 143.1664 - loss: 44662.0938 - reconstruction_loss: 44518.9258

Epoch 8/400

1/1 **0s** 200ms/step - kl_loss: 123.6908 - loss: 44267.0742 - reconstruction_loss: 44143.3828

Epoch 9/400

1/1 **0s** 308ms/step - kl_loss: 131.9148 - loss: 43674.8359 - reconstruction_loss: 43542.9219

Epoch 10/400

1/1 **1s** 593ms/step - kl_loss: 170.9884 - loss: 42697.8477 - reconstruction_loss: 42526.8594

Epoch 11/400

1/1 **0s** 229ms/step - kl_loss: 255.5348 - loss: 40971.1055 - reconstruction_loss: 40715.5703

Epoch 12/400

1/1 **0s** 204ms/step - kl_loss: 452.8618 - loss: 37868.6602 - reconstruction_loss: 37415.7969

Epoch 13/400

1/1 **0s** 201ms/step - kl_loss: 864.2040 - loss: 32967.8203 - reconstruction_loss: 32103.6172

Epoch 14/400

1/1 **0s** 203ms/step - kl_loss: 1657.5676 - loss: 26984.0059 - reconstruction_loss: 25326.4375

Epoch 15/400

1/1 **0s** 202ms/step - kl_loss: 3109.7419 - loss: 22748.7520 - reconstruction_loss: 19639.0098

Epoch 16/400

1/1 **0s** 203ms/step - kl_loss: 5166.3970 - loss: 22955.2930 - reconstruction_loss: 17788.8965

Epoch 17/400

1/1 **0s** 205ms/step - kl_loss: 6214.5254 - loss: 24114.0977 - reconstruction_loss: 17899.5723

Epoch 18/400

1/1 **0s** 205ms/step - kl_loss: 5891.2876 - loss: 23551.0918 - reconstruction_loss: 17659.8047

Epoch 19/400

```
1/1 _____ 0s 203ms/step - kl_loss: 4826.8462 - loss: 21746.04
30 - reconstruction_loss: 16919.1973
Epoch 20/400
1/1 _____ 0s 200ms/step - kl_loss: 3585.8745 - loss: 19636.42
77 - reconstruction_loss: 16050.5527
Epoch 21/400
1/1 _____ 0s 201ms/step - kl_loss: 2478.0024 - loss: 17863.75
78 - reconstruction_loss: 15385.7559
Epoch 22/400
1/1 _____ 0s 202ms/step - kl_loss: 1629.0715 - loss: 16736.36
72 - reconstruction_loss: 15107.2949
Epoch 23/400
1/1 _____ 0s 203ms/step - kl_loss: 1046.4292 - loss: 16289.52
73 - reconstruction_loss: 15243.0986
Epoch 24/400
1/1 _____ 0s 205ms/step - kl_loss: 680.3646 - loss: 16364.934
6 - reconstruction_loss: 15684.5703
Epoch 25/400
1/1 _____ 0s 200ms/step - kl_loss: 468.5663 - loss: 16663.154
3 - reconstruction_loss: 16194.5879
Epoch 26/400
1/1 _____ 0s 199ms/step - kl_loss: 357.9797 - loss: 16840.582
0 - reconstruction_loss: 16482.6016
Epoch 27/400
1/1 _____ 0s 203ms/step - kl_loss: 311.3405 - loss: 16694.615
2 - reconstruction_loss: 16383.2754
Epoch 28/400
1/1 _____ 0s 204ms/step - kl_loss: 305.4317 - loss: 16283.878
9 - reconstruction_loss: 15978.4473
Epoch 29/400
1/1 _____ 0s 205ms/step - kl_loss: 326.1592 - loss: 15821.061
5 - reconstruction_loss: 15494.9023
Epoch 30/400
1/1 _____ 0s 202ms/step - kl_loss: 364.1149 - loss: 15470.718
8 - reconstruction_loss: 15106.6035
Epoch 31/400
1/1 _____ 0s 204ms/step - kl_loss: 411.2558 - loss: 15272.354
5 - reconstruction_loss: 14861.0986
Epoch 32/400
1/1 _____ 0s 204ms/step - kl_loss: 460.1457 - loss: 15189.540
0 - reconstruction_loss: 14729.3945
Epoch 33/400
1/1 _____ 0s 206ms/step - kl_loss: 504.0616 - loss: 15172.136
7 - reconstruction_loss: 14668.0752
Epoch 34/400
1/1 _____ 0s 203ms/step - kl_loss: 537.3657 - loss: 15180.531
2 - reconstruction_loss: 14643.1660
Epoch 35/400
1/1 _____ 0s 205ms/step - kl_loss: 555.9710 - loss: 15187.367
2 - reconstruction_loss: 14631.3965
Epoch 36/400
1/1 _____ 0s 205ms/step - kl_loss: 557.8525 - loss: 15174.976
6 - reconstruction_loss: 14617.1240
Epoch 37/400
1/1 _____ 0s 204ms/step - kl_loss: 543.0895 - loss: 15133.945
3 - reconstruction_loss: 14590.8555
```

Epoch 38/400
1/1 0s 204ms/step - kl_loss: 513.7029 - loss: 15062.210
0 - reconstruction_loss: 14548.5068
Epoch 39/400
1/1 0s 203ms/step - kl_loss: 473.1830 - loss: 14964.713
9 - reconstruction_loss: 14491.5312
Epoch 40/400
1/1 0s 205ms/step - kl_loss: 425.7643 - loss: 14851.311
5 - reconstruction_loss: 14425.5469
Epoch 41/400
1/1 0s 204ms/step - kl_loss: 375.6823 - loss: 14734.371
1 - reconstruction_loss: 14358.6885
Epoch 42/400
1/1 0s 221ms/step - kl_loss: 326.5961 - loss: 14626.401
4 - reconstruction_loss: 14299.8057
Epoch 43/400
1/1 0s 229ms/step - kl_loss: 281.2594 - loss: 14536.590
8 - reconstruction_loss: 14255.3311
Epoch 44/400
1/1 0s 217ms/step - kl_loss: 241.4303 - loss: 14469.751
0 - reconstruction_loss: 14228.3203
Epoch 45/400
1/1 0s 219ms/step - kl_loss: 207.9783 - loss: 14425.615
2 - reconstruction_loss: 14217.6367
Epoch 46/400
1/1 0s 220ms/step - kl_loss: 181.0938 - loss: 14398.868
2 - reconstruction_loss: 14217.7744
Epoch 47/400
1/1 0s 234ms/step - kl_loss: 160.5065 - loss: 14381.391
6 - reconstruction_loss: 14220.8848
Epoch 48/400
1/1 0s 236ms/step - kl_loss: 145.7024 - loss: 14363.353
5 - reconstruction_loss: 14217.6514
Epoch 49/400
1/1 0s 219ms/step - kl_loss: 136.0284 - loss: 14338.170
9 - reconstruction_loss: 14202.1426
Epoch 50/400
1/1 0s 231ms/step - kl_loss: 130.7866 - loss: 14302.824
2 - reconstruction_loss: 14172.0381
Epoch 51/400
1/1 0s 218ms/step - kl_loss: 129.4414 - loss: 14258.615
2 - reconstruction_loss: 14129.1738
Epoch 52/400
1/1 0s 205ms/step - kl_loss: 132.4949 - loss: 14211.458
0 - reconstruction_loss: 14078.9629
Epoch 53/400
1/1 0s 204ms/step - kl_loss: 138.7935 - loss: 14172.252
0 - reconstruction_loss: 14033.4580
Epoch 54/400
1/1 0s 203ms/step - kl_loss: 147.6203 - loss: 14149.233
4 - reconstruction_loss: 14001.6133
Epoch 55/400
1/1 0s 202ms/step - kl_loss: 155.7080 - loss: 14142.895
5 - reconstruction_loss: 13987.1875
Epoch 56/400
1/1 0s 205ms/step - kl_loss: 156.7447 - loss: 14137.767

```
6 - reconstruction_loss: 13981.0225
Epoch 57/400
1/1 0s 203ms/step - kl_loss: 151.9904 - loss: 14126.279
3 - reconstruction_loss: 13974.2891
Epoch 58/400
1/1 0s 205ms/step - kl_loss: 143.8793 - loss: 14107.377
9 - reconstruction_loss: 13963.4990
Epoch 59/400
1/1 0s 204ms/step - kl_loss: 133.9939 - loss: 14084.515
6 - reconstruction_loss: 13950.5215
Epoch 60/400
1/1 0s 195ms/step - kl_loss: 122.3180 - loss: 14061.818
4 - reconstruction_loss: 13939.5000
Epoch 61/400
1/1 0s 207ms/step - kl_loss: 111.0050 - loss: 14045.690
4 - reconstruction_loss: 13934.6855
Epoch 62/400
1/1 0s 210ms/step - kl_loss: 103.8602 - loss: 14035.370
1 - reconstruction_loss: 13931.5098
Epoch 63/400
1/1 0s 205ms/step - kl_loss: 105.1215 - loss: 14018.877
0 - reconstruction_loss: 13913.7559
Epoch 64/400
1/1 0s 205ms/step - kl_loss: 111.5724 - loss: 14000.989
3 - reconstruction_loss: 13889.4170
Epoch 65/400
1/1 0s 208ms/step - kl_loss: 120.3136 - loss: 13988.826
2 - reconstruction_loss: 13868.5127
Epoch 66/400
1/1 0s 208ms/step - kl_loss: 117.8596 - loss: 13971.386
7 - reconstruction_loss: 13853.5273
Epoch 67/400
1/1 0s 207ms/step - kl_loss: 111.9138 - loss: 13953.066
4 - reconstruction_loss: 13841.1523
Epoch 68/400
1/1 0s 207ms/step - kl_loss: 108.3061 - loss: 13936.761
7 - reconstruction_loss: 13828.4561
Epoch 69/400
1/1 0s 209ms/step - kl_loss: 108.8290 - loss: 13918.711
9 - reconstruction_loss: 13809.8828
Epoch 70/400
1/1 0s 208ms/step - kl_loss: 114.0708 - loss: 13897.216
8 - reconstruction_loss: 13783.1465
Epoch 71/400
1/1 0s 210ms/step - kl_loss: 122.4123 - loss: 13875.433
6 - reconstruction_loss: 13753.0215
Epoch 72/400
1/1 0s 209ms/step - kl_loss: 121.7130 - loss: 13849.539
1 - reconstruction_loss: 13727.8262
Epoch 73/400
1/1 0s 208ms/step - kl_loss: 116.9773 - loss: 13821.665
0 - reconstruction_loss: 13704.6875
Epoch 74/400
1/1 0s 206ms/step - kl_loss: 114.6693 - loss: 13792.348
6 - reconstruction_loss: 13677.6797
Epoch 75/400
```

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1/1 _____ 0s 208ms/step - kl_loss: 115.7033 - loss: 13761.837
9 - reconstruction_loss: 13646.1348
Epoch 76/400
1/1 _____ 0s 212ms/step - kl_loss: 123.2235 - loss: 13727.312
5 - reconstruction_loss: 13604.0889
Epoch 77/400
1/1 _____ 0s 215ms/step - kl_loss: 124.4559 - loss: 13689.922
9 - reconstruction_loss: 13565.4668
Epoch 78/400
1/1 _____ 0s 210ms/step - kl_loss: 121.5220 - loss: 13647.951
2 - reconstruction_loss: 13526.4287
Epoch 79/400
1/1 _____ 0s 210ms/step - kl_loss: 121.2788 - loss: 13603.162
1 - reconstruction_loss: 13481.8828
Epoch 80/400
1/1 _____ 0s 207ms/step - kl_loss: 124.5410 - loss: 13554.870
1 - reconstruction_loss: 13430.3291
Epoch 81/400
1/1 _____ 0s 212ms/step - kl_loss: 131.9117 - loss: 13500.972
7 - reconstruction_loss: 13369.0605
Epoch 82/400
1/1 _____ 0s 207ms/step - kl_loss: 131.5116 - loss: 13440.334
0 - reconstruction_loss: 13308.8223
Epoch 83/400
1/1 _____ 0s 210ms/step - kl_loss: 131.4054 - loss: 13374.727
5 - reconstruction_loss: 13243.3223
Epoch 84/400
1/1 _____ 0s 208ms/step - kl_loss: 137.5096 - loss: 13302.754
9 - reconstruction_loss: 13165.2451
Epoch 85/400
1/1 _____ 0s 211ms/step - kl_loss: 145.6616 - loss: 13223.682
6 - reconstruction_loss: 13078.0215
Epoch 86/400
1/1 _____ 0s 209ms/step - kl_loss: 145.1812 - loss: 13136.296
9 - reconstruction_loss: 12991.1152
Epoch 87/400
1/1 _____ 0s 209ms/step - kl_loss: 151.5346 - loss: 13041.901
4 - reconstruction_loss: 12890.3672
Epoch 88/400
1/1 _____ 0s 209ms/step - kl_loss: 167.1934 - loss: 12940.959
0 - reconstruction_loss: 12773.7656
Epoch 89/400
1/1 _____ 0s 211ms/step - kl_loss: 153.1131 - loss: 12837.084
0 - reconstruction_loss: 12683.9707
Epoch 90/400
1/1 _____ 0s 210ms/step - kl_loss: 178.9375 - loss: 12711.510
7 - reconstruction_loss: 12532.5732
Epoch 91/400
1/1 _____ 0s 209ms/step - kl_loss: 193.9419 - loss: 12590.924
8 - reconstruction_loss: 12396.9824
Epoch 92/400
1/1 _____ 0s 210ms/step - kl_loss: 184.2044 - loss: 12457.237
3 - reconstruction_loss: 12273.0332
Epoch 93/400
1/1 _____ 0s 208ms/step - kl_loss: 193.0022 - loss: 12323.207
0 - reconstruction_loss: 12130.2051
```

Epoch 94/400
1/1 0s 208ms/step - kl_loss: 221.2339 - loss: 12187.669
9 - reconstruction_loss: 11966.4355
Epoch 95/400
1/1 0s 210ms/step - kl_loss: 227.0536 - loss: 12051.597
7 - reconstruction_loss: 11824.5439
Epoch 96/400
1/1 0s 207ms/step - kl_loss: 220.8297 - loss: 11922.255
9 - reconstruction_loss: 11701.4258
Epoch 97/400
1/1 0s 210ms/step - kl_loss: 234.3167 - loss: 11799.450
2 - reconstruction_loss: 11565.1338
Epoch 98/400
1/1 0s 215ms/step - kl_loss: 257.3991 - loss: 11692.637
7 - reconstruction_loss: 11435.2383
Epoch 99/400
1/1 0s 233ms/step - kl_loss: 247.2883 - loss: 11593.668
0 - reconstruction_loss: 11346.3799
Epoch 100/400
1/1 0s 251ms/step - kl_loss: 234.3896 - loss: 11515.668
0 - reconstruction_loss: 11281.2783
Epoch 101/400
1/1 0s 223ms/step - kl_loss: 244.9865 - loss: 11446.978
5 - reconstruction_loss: 11201.9922
Epoch 102/400
1/1 0s 225ms/step - kl_loss: 233.2129 - loss: 11391.960
9 - reconstruction_loss: 11158.7480
Epoch 103/400
1/1 0s 225ms/step - kl_loss: 205.2442 - loss: 11346.957
0 - reconstruction_loss: 11141.7129
Epoch 104/400
1/1 0s 236ms/step - kl_loss: 203.1094 - loss: 11305.738
3 - reconstruction_loss: 11102.6289
Epoch 105/400
1/1 0s 247ms/step - kl_loss: 179.9867 - loss: 11268.270
5 - reconstruction_loss: 11088.2842
Epoch 106/400
1/1 0s 236ms/step - kl_loss: 165.3762 - loss: 11233.638
7 - reconstruction_loss: 11068.2627
Epoch 107/400
1/1 0s 221ms/step - kl_loss: 152.6980 - loss: 11200.223
6 - reconstruction_loss: 11047.5254
Epoch 108/400
1/1 0s 210ms/step - kl_loss: 131.7663 - loss: 11171.383
8 - reconstruction_loss: 11039.6172
Epoch 109/400
1/1 0s 217ms/step - kl_loss: 148.3844 - loss: 11160.613
3 - reconstruction_loss: 11012.2285
Epoch 110/400
1/1 0s 209ms/step - kl_loss: 115.9588 - loss: 11111.598
6 - reconstruction_loss: 10995.6396
Epoch 111/400
1/1 0s 209ms/step - kl_loss: 106.0462 - loss: 11092.938
5 - reconstruction_loss: 10986.8926
Epoch 112/400
1/1 0s 211ms/step - kl_loss: 117.2123 - loss: 11066.469

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7 - reconstruction_loss: 10949.2578
Epoch 113/400
1/1 0s 209ms/step - kl_loss: 112.1756 - loss: 11046.493
2 - reconstruction_loss: 10934.3174
Epoch 114/400
1/1 0s 211ms/step - kl_loss: 94.7244 - loss: 11022.2148
- reconstruction_loss: 10927.4902
Epoch 115/400
1/1 0s 210ms/step - kl_loss: 86.8641 - loss: 11005.1846
- reconstruction_loss: 10918.3203
Epoch 116/400
1/1 0s 212ms/step - kl_loss: 89.7702 - loss: 10981.5264
- reconstruction_loss: 10891.7559
Epoch 117/400
1/1 0s 208ms/step - kl_loss: 89.3734 - loss: 10971.2930
- reconstruction_loss: 10881.9199
Epoch 118/400
1/1 0s 208ms/step - kl_loss: 81.8568 - loss: 10953.2715
- reconstruction_loss: 10871.4150
Epoch 119/400
1/1 0s 209ms/step - kl_loss: 76.2040 - loss: 10939.9365
- reconstruction_loss: 10863.7324
Epoch 120/400
1/1 0s 210ms/step - kl_loss: 74.3409 - loss: 10928.5361
- reconstruction_loss: 10854.1953
Epoch 121/400
1/1 0s 207ms/step - kl_loss: 76.1833 - loss: 10915.6143
- reconstruction_loss: 10839.4307
Epoch 122/400
1/1 0s 209ms/step - kl_loss: 77.1628 - loss: 10905.3076
- reconstruction_loss: 10828.1445
Epoch 123/400
1/1 0s 209ms/step - kl_loss: 75.2587 - loss: 10894.9561
- reconstruction_loss: 10819.6973
Epoch 124/400
1/1 0s 210ms/step - kl_loss: 72.2830 - loss: 10883.7891
- reconstruction_loss: 10811.5059
Epoch 125/400
1/1 0s 209ms/step - kl_loss: 69.6355 - loss: 10879.6689
- reconstruction_loss: 10810.0332
Epoch 126/400
1/1 0s 208ms/step - kl_loss: 73.1277 - loss: 10866.1006
- reconstruction_loss: 10792.9727
Epoch 127/400
1/1 0s 210ms/step - kl_loss: 75.7074 - loss: 10860.8623
- reconstruction_loss: 10785.1553
Epoch 128/400
1/1 0s 207ms/step - kl_loss: 72.4755 - loss: 10849.3662
- reconstruction_loss: 10776.8906
Epoch 129/400
1/1 0s 216ms/step - kl_loss: 67.3318 - loss: 10847.3105
- reconstruction_loss: 10779.9785
Epoch 130/400
1/1 0s 211ms/step - kl_loss: 69.2406 - loss: 10832.7139
- reconstruction_loss: 10763.4736
Epoch 131/400
```

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1/1 _____ 0s 208ms/step - kl_loss: 71.2891 - loss: 10825.4199
- reconstruction_loss: 10754.1309
Epoch 132/400
1/1 _____ 0s 211ms/step - kl_loss: 71.8276 - loss: 10821.3545
- reconstruction_loss: 10749.5264
Epoch 133/400
1/1 _____ 0s 217ms/step - kl_loss: 68.2971 - loss: 10808.4111
- reconstruction_loss: 10740.1143
Epoch 134/400
1/1 _____ 0s 210ms/step - kl_loss: 65.0262 - loss: 10808.3174
- reconstruction_loss: 10743.2910
Epoch 135/400
1/1 _____ 0s 209ms/step - kl_loss: 66.8577 - loss: 10797.9297
- reconstruction_loss: 10731.0723
Epoch 136/400
1/1 _____ 0s 209ms/step - kl_loss: 66.6382 - loss: 10791.2812
- reconstruction_loss: 10724.6436
Epoch 137/400
1/1 _____ 0s 210ms/step - kl_loss: 62.9973 - loss: 10784.5254
- reconstruction_loss: 10721.5283
Epoch 138/400
1/1 _____ 0s 208ms/step - kl_loss: 62.6195 - loss: 10776.9121
- reconstruction_loss: 10714.2930
Epoch 139/400
1/1 _____ 0s 207ms/step - kl_loss: 64.4466 - loss: 10771.3467
- reconstruction_loss: 10706.9004
Epoch 140/400
1/1 _____ 0s 210ms/step - kl_loss: 63.7601 - loss: 10768.9746
- reconstruction_loss: 10705.2148
Epoch 141/400
1/1 _____ 0s 206ms/step - kl_loss: 61.0869 - loss: 10762.1992
- reconstruction_loss: 10701.1123
Epoch 142/400
1/1 _____ 0s 208ms/step - kl_loss: 60.2829 - loss: 10755.1133
- reconstruction_loss: 10694.8301
Epoch 143/400
1/1 _____ 0s 207ms/step - kl_loss: 60.4785 - loss: 10750.0312
- reconstruction_loss: 10689.5527
Epoch 144/400
1/1 _____ 0s 208ms/step - kl_loss: 58.7318 - loss: 10743.3438
- reconstruction_loss: 10684.6123
Epoch 145/400
1/1 _____ 0s 209ms/step - kl_loss: 56.3292 - loss: 10742.1465
- reconstruction_loss: 10685.8174
Epoch 146/400
1/1 _____ 0s 209ms/step - kl_loss: 57.2332 - loss: 10736.3115
- reconstruction_loss: 10679.0781
Epoch 147/400
1/1 _____ 0s 210ms/step - kl_loss: 60.1923 - loss: 10738.3643
- reconstruction_loss: 10678.1719
Epoch 148/400
1/1 _____ 0s 210ms/step - kl_loss: 57.4879 - loss: 10729.0439
- reconstruction_loss: 10671.5557
Epoch 149/400
1/1 _____ 0s 208ms/step - kl_loss: 50.7837 - loss: 10723.6670
- reconstruction_loss: 10672.8828
```

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Epoch 150/400
1/1 0s 209ms/step - kl_loss: 49.3464 - loss: 10734.4033
- reconstruction_loss: 10685.0566
Epoch 151/400
1/1 0s 215ms/step - kl_loss: 55.9141 - loss: 10712.8877
- reconstruction_loss: 10656.9736
Epoch 152/400
1/1 0s 208ms/step - kl_loss: 57.8059 - loss: 10731.2480
- reconstruction_loss: 10673.4424
Epoch 153/400
1/1 0s 218ms/step - kl_loss: 51.6409 - loss: 10698.5332
- reconstruction_loss: 10646.8926
Epoch 154/400
1/1 0s 226ms/step - kl_loss: 46.1902 - loss: 10711.7178
- reconstruction_loss: 10665.5273
Epoch 155/400
1/1 0s 218ms/step - kl_loss: 47.6168 - loss: 10702.6016
- reconstruction_loss: 10654.9844
Epoch 156/400
1/1 0s 226ms/step - kl_loss: 53.4043 - loss: 10693.0244
- reconstruction_loss: 10639.6201
Epoch 157/400
1/1 0s 232ms/step - kl_loss: 54.4027 - loss: 10708.2949
- reconstruction_loss: 10653.8926
Epoch 158/400
1/1 0s 230ms/step - kl_loss: 48.6619 - loss: 10678.0557
- reconstruction_loss: 10629.3936
Epoch 159/400
1/1 0s 230ms/step - kl_loss: 44.9337 - loss: 10689.9775
- reconstruction_loss: 10645.0439
Epoch 160/400
1/1 0s 229ms/step - kl_loss: 47.1053 - loss: 10675.4463
- reconstruction_loss: 10628.3408
Epoch 161/400
1/1 0s 228ms/step - kl_loss: 49.2082 - loss: 10669.0674
- reconstruction_loss: 10619.8594
Epoch 162/400
1/1 0s 231ms/step - kl_loss: 49.3159 - loss: 10674.2412
- reconstruction_loss: 10624.9258
Epoch 163/400
1/1 0s 301ms/step - kl_loss: 45.8027 - loss: 10663.7871
- reconstruction_loss: 10617.9844
Epoch 164/400
1/1 0s 391ms/step - kl_loss: 45.2247 - loss: 10656.8438
- reconstruction_loss: 10611.6191
Epoch 165/400
1/1 0s 381ms/step - kl_loss: 45.6759 - loss: 10650.2852
- reconstruction_loss: 10604.6094
Epoch 166/400
1/1 0s 217ms/step - kl_loss: 45.7889 - loss: 10649.8926
- reconstruction_loss: 10604.1035
Epoch 167/400
1/1 0s 297ms/step - kl_loss: 45.4983 - loss: 10650.0244
- reconstruction_loss: 10604.5264
Epoch 168/400
1/1 0s 318ms/step - kl_loss: 42.9189 - loss: 10655.6299
```

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- reconstruction_loss: 10612.7109
Epoch 169/400
1/1 0s 355ms/step - kl_loss: 44.8374 - loss: 10638.1396
- reconstruction_loss: 10593.3027
Epoch 170/400
1/1 0s 240ms/step - kl_loss: 43.7124 - loss: 10646.0244
- reconstruction_loss: 10602.3115
Epoch 171/400
1/1 0s 209ms/step - kl_loss: 40.2801 - loss: 10632.8799
- reconstruction_loss: 10592.5996
Epoch 172/400
1/1 0s 208ms/step - kl_loss: 39.6898 - loss: 10640.2246
- reconstruction_loss: 10600.5352
Epoch 173/400
1/1 0s 221ms/step - kl_loss: 42.8356 - loss: 10621.9648
- reconstruction_loss: 10579.1289
Epoch 174/400
1/1 0s 209ms/step - kl_loss: 44.6232 - loss: 10636.6318
- reconstruction_loss: 10592.0088
Epoch 175/400
1/1 0s 207ms/step - kl_loss: 42.2811 - loss: 10622.2539
- reconstruction_loss: 10579.9727
Epoch 176/400
1/1 0s 209ms/step - kl_loss: 38.7941 - loss: 10623.8535
- reconstruction_loss: 10585.0596
Epoch 177/400
1/1 0s 209ms/step - kl_loss: 38.9823 - loss: 10614.0703
- reconstruction_loss: 10575.0879
Epoch 178/400
1/1 0s 206ms/step - kl_loss: 41.7010 - loss: 10607.3760
- reconstruction_loss: 10565.6748
Epoch 179/400
1/1 0s 211ms/step - kl_loss: 42.8836 - loss: 10614.5811
- reconstruction_loss: 10571.6973
Epoch 180/400
1/1 0s 209ms/step - kl_loss: 40.3175 - loss: 10599.2188
- reconstruction_loss: 10558.9014
Epoch 181/400
1/1 0s 208ms/step - kl_loss: 37.5796 - loss: 10605.7354
- reconstruction_loss: 10568.1562
Epoch 182/400
1/1 0s 217ms/step - kl_loss: 37.8842 - loss: 10599.0732
- reconstruction_loss: 10561.1895
Epoch 183/400
1/1 0s 209ms/step - kl_loss: 41.0517 - loss: 10599.9463
- reconstruction_loss: 10558.8945
Epoch 184/400
1/1 0s 207ms/step - kl_loss: 40.2769 - loss: 10594.5430
- reconstruction_loss: 10554.2656
Epoch 185/400
1/1 0s 211ms/step - kl_loss: 36.9220 - loss: 10595.3008
- reconstruction_loss: 10558.3789
Epoch 186/400
1/1 0s 217ms/step - kl_loss: 36.5201 - loss: 10577.9531
- reconstruction_loss: 10541.4326
Epoch 187/400
```

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1/1 _____ 0s 212ms/step - kl_loss: 37.3813 - loss: 10575.0332
- reconstruction_loss: 10537.6523
Epoch 188/400
1/1 _____ 0s 209ms/step - kl_loss: 37.5492 - loss: 10574.0352
- reconstruction_loss: 10536.4863
Epoch 189/400
1/1 _____ 0s 206ms/step - kl_loss: 37.4357 - loss: 10576.0010
- reconstruction_loss: 10538.5654
Epoch 190/400
1/1 _____ 0s 208ms/step - kl_loss: 37.2484 - loss: 10562.7275
- reconstruction_loss: 10525.4795
Epoch 191/400
1/1 _____ 0s 209ms/step - kl_loss: 36.8816 - loss: 10567.0459
- reconstruction_loss: 10530.1641
Epoch 192/400
1/1 _____ 0s 204ms/step - kl_loss: 37.3700 - loss: 10561.1689
- reconstruction_loss: 10523.7988
Epoch 193/400
1/1 _____ 0s 207ms/step - kl_loss: 36.6846 - loss: 10556.8740
- reconstruction_loss: 10520.1895
Epoch 194/400
1/1 _____ 0s 212ms/step - kl_loss: 35.1338 - loss: 10547.8818
- reconstruction_loss: 10512.7480
Epoch 195/400
1/1 _____ 0s 206ms/step - kl_loss: 34.0257 - loss: 10546.9004
- reconstruction_loss: 10512.8750
Epoch 196/400
1/1 _____ 0s 196ms/step - kl_loss: 35.2343 - loss: 10539.6182
- reconstruction_loss: 10504.3838
Epoch 197/400
1/1 _____ 0s 208ms/step - kl_loss: 36.0786 - loss: 10553.5664
- reconstruction_loss: 10517.4883
Epoch 198/400
1/1 _____ 0s 206ms/step - kl_loss: 34.0513 - loss: 10538.4766
- reconstruction_loss: 10504.4258
Epoch 199/400
1/1 _____ 0s 206ms/step - kl_loss: 31.2809 - loss: 10550.8721
- reconstruction_loss: 10519.5908
Epoch 200/400
1/1 _____ 0s 205ms/step - kl_loss: 33.3873 - loss: 10535.6387
- reconstruction_loss: 10502.2510
Epoch 201/400
1/1 _____ 0s 206ms/step - kl_loss: 37.4171 - loss: 10557.1436
- reconstruction_loss: 10519.7266
Epoch 202/400
1/1 _____ 0s 206ms/step - kl_loss: 34.8658 - loss: 10522.3389
- reconstruction_loss: 10487.4727
Epoch 203/400
1/1 _____ 0s 208ms/step - kl_loss: 31.2031 - loss: 10530.9248
- reconstruction_loss: 10499.7217
Epoch 204/400
1/1 _____ 0s 208ms/step - kl_loss: 31.7018 - loss: 10518.9287
- reconstruction_loss: 10487.2266
Epoch 205/400
1/1 _____ 0s 222ms/step - kl_loss: 34.9120 - loss: 10517.9648
- reconstruction_loss: 10483.0527
```

```
Epoch 206/400
1/1 _____ 0s 222ms/step - kl_loss: 34.8217 - loss: 10521.7773
- reconstruction_loss: 10486.9561
Epoch 207/400
1/1 _____ 0s 229ms/step - kl_loss: 30.8739 - loss: 10504.2432
- reconstruction_loss: 10473.3691
Epoch 208/400
1/1 _____ 0s 217ms/step - kl_loss: 30.1783 - loss: 10526.9131
- reconstruction_loss: 10496.7344
Epoch 209/400
1/1 _____ 0s 227ms/step - kl_loss: 35.1944 - loss: 10521.4941
- reconstruction_loss: 10486.2998
Epoch 210/400
1/1 _____ 0s 233ms/step - kl_loss: 34.3075 - loss: 10507.0635
- reconstruction_loss: 10472.7559
Epoch 211/400
1/1 _____ 0s 232ms/step - kl_loss: 29.8407 - loss: 10488.2441
- reconstruction_loss: 10458.4033
Epoch 212/400
1/1 _____ 0s 224ms/step - kl_loss: 28.6213 - loss: 10500.3926
- reconstruction_loss: 10471.7715
Epoch 213/400
1/1 _____ 0s 237ms/step - kl_loss: 31.1046 - loss: 10472.8691
- reconstruction_loss: 10441.7646
Epoch 214/400
1/1 _____ 0s 235ms/step - kl_loss: 33.3817 - loss: 10487.3975
- reconstruction_loss: 10454.0156
Epoch 215/400
1/1 _____ 0s 212ms/step - kl_loss: 31.7176 - loss: 10474.4199
- reconstruction_loss: 10442.7021
Epoch 216/400
1/1 _____ 0s 205ms/step - kl_loss: 28.6632 - loss: 10470.9941
- reconstruction_loss: 10442.3311
Epoch 217/400
1/1 _____ 0s 210ms/step - kl_loss: 29.1633 - loss: 10470.1885
- reconstruction_loss: 10441.0254
Epoch 218/400
1/1 _____ 0s 208ms/step - kl_loss: 32.3389 - loss: 10470.2461
- reconstruction_loss: 10437.9072
Epoch 219/400
1/1 _____ 0s 213ms/step - kl_loss: 32.7996 - loss: 10511.3506
- reconstruction_loss: 10478.5508
Epoch 220/400
1/1 _____ 0s 214ms/step - kl_loss: 28.0400 - loss: 10456.3301
- reconstruction_loss: 10428.2900
Epoch 221/400
1/1 _____ 0s 213ms/step - kl_loss: 27.2245 - loss: 10473.3984
- reconstruction_loss: 10446.1738
Epoch 222/400
1/1 _____ 0s 218ms/step - kl_loss: 31.5116 - loss: 10446.7754
- reconstruction_loss: 10415.2637
Epoch 223/400
1/1 _____ 0s 207ms/step - kl_loss: 33.1143 - loss: 10473.5039
- reconstruction_loss: 10440.3896
Epoch 224/400
1/1 _____ 0s 206ms/step - kl_loss: 29.1030 - loss: 10444.2871
```

```
- reconstruction_loss: 10415.1846
Epoch 225/400
1/1 0s 206ms/step - kl_loss: 27.4970 - loss: 10459.7852
- reconstruction_loss: 10432.2881
Epoch 226/400
1/1 0s 208ms/step - kl_loss: 30.4637 - loss: 10423.9502
- reconstruction_loss: 10393.4863
Epoch 227/400
1/1 0s 210ms/step - kl_loss: 33.0434 - loss: 10436.2422
- reconstruction_loss: 10403.1992
Epoch 228/400
1/1 0s 210ms/step - kl_loss: 31.0747 - loss: 10427.2988
- reconstruction_loss: 10396.2246
Epoch 229/400
1/1 0s 208ms/step - kl_loss: 28.5395 - loss: 10415.6211
- reconstruction_loss: 10387.0820
Epoch 230/400
1/1 0s 210ms/step - kl_loss: 28.5887 - loss: 10427.8525
- reconstruction_loss: 10399.2637
Epoch 231/400
1/1 0s 213ms/step - kl_loss: 32.0639 - loss: 10418.4648
- reconstruction_loss: 10386.4014
Epoch 232/400
1/1 0s 206ms/step - kl_loss: 31.9310 - loss: 10398.6367
- reconstruction_loss: 10366.7061
Epoch 233/400
1/1 0s 206ms/step - kl_loss: 28.7693 - loss: 10392.9072
- reconstruction_loss: 10364.1377
Epoch 234/400
1/1 0s 205ms/step - kl_loss: 27.4784 - loss: 10404.2061
- reconstruction_loss: 10376.7275
Epoch 235/400
1/1 0s 207ms/step - kl_loss: 29.9267 - loss: 10385.4229
- reconstruction_loss: 10355.4961
Epoch 236/400
1/1 0s 209ms/step - kl_loss: 31.3145 - loss: 10403.8955
- reconstruction_loss: 10372.5811
Epoch 237/400
1/1 0s 211ms/step - kl_loss: 28.3059 - loss: 10372.1924
- reconstruction_loss: 10343.8867
Epoch 238/400
1/1 0s 207ms/step - kl_loss: 26.4165 - loss: 10390.6299
- reconstruction_loss: 10364.2129
Epoch 239/400
1/1 0s 205ms/step - kl_loss: 28.6556 - loss: 10364.2998
- reconstruction_loss: 10335.6445
Epoch 240/400
1/1 0s 208ms/step - kl_loss: 31.7970 - loss: 10397.5664
- reconstruction_loss: 10365.7695
Epoch 241/400
1/1 0s 207ms/step - kl_loss: 29.3530 - loss: 10349.5967
- reconstruction_loss: 10320.2441
Epoch 242/400
1/1 0s 206ms/step - kl_loss: 26.2586 - loss: 10381.9805
- reconstruction_loss: 10355.7217
Epoch 243/400
```

```
1/1 _____ 0s 208ms/step - kl_loss: 27.5551 - loss: 10347.8906
- reconstruction_loss: 10320.3359
Epoch 244/400
1/1 _____ 0s 208ms/step - kl_loss: 30.9875 - loss: 10376.3350
- reconstruction_loss: 10345.3477
Epoch 245/400
1/1 _____ 0s 206ms/step - kl_loss: 30.1428 - loss: 10345.2148
- reconstruction_loss: 10315.0723
Epoch 246/400
1/1 _____ 0s 206ms/step - kl_loss: 26.5049 - loss: 10363.2236
- reconstruction_loss: 10336.7188
Epoch 247/400
1/1 _____ 0s 209ms/step - kl_loss: 26.9407 - loss: 10333.6670
- reconstruction_loss: 10306.7266
Epoch 248/400
1/1 _____ 0s 207ms/step - kl_loss: 30.1564 - loss: 10333.5664
- reconstruction_loss: 10303.4102
Epoch 249/400
1/1 _____ 0s 215ms/step - kl_loss: 31.1507 - loss: 10348.7578
- reconstruction_loss: 10317.6074
Epoch 250/400
1/1 _____ 0s 209ms/step - kl_loss: 27.5946 - loss: 10318.7354
- reconstruction_loss: 10291.1406
Epoch 251/400
1/1 _____ 0s 206ms/step - kl_loss: 26.1818 - loss: 10319.0215
- reconstruction_loss: 10292.8398
Epoch 252/400
1/1 _____ 0s 207ms/step - kl_loss: 27.9655 - loss: 10300.8877
- reconstruction_loss: 10272.9219
Epoch 253/400
1/1 _____ 0s 219ms/step - kl_loss: 30.5273 - loss: 10318.4336
- reconstruction_loss: 10287.9062
Epoch 254/400
1/1 _____ 0s 206ms/step - kl_loss: 29.7975 - loss: 10288.3447
- reconstruction_loss: 10258.5469
Epoch 255/400
1/1 _____ 0s 206ms/step - kl_loss: 27.2268 - loss: 10299.0859
- reconstruction_loss: 10271.8594
Epoch 256/400
1/1 _____ 0s 208ms/step - kl_loss: 26.5275 - loss: 10298.5674
- reconstruction_loss: 10272.0400
Epoch 257/400
1/1 _____ 0s 211ms/step - kl_loss: 29.0893 - loss: 10291.6318
- reconstruction_loss: 10262.5430
Epoch 258/400
1/1 _____ 0s 208ms/step - kl_loss: 29.5388 - loss: 10271.0801
- reconstruction_loss: 10241.5410
Epoch 259/400
1/1 _____ 0s 209ms/step - kl_loss: 27.4640 - loss: 10268.2725
- reconstruction_loss: 10240.8086
Epoch 260/400
1/1 _____ 0s 211ms/step - kl_loss: 27.4766 - loss: 10260.9805
- reconstruction_loss: 10233.5039
Epoch 261/400
1/1 _____ 0s 209ms/step - kl_loss: 29.3576 - loss: 10265.5205
- reconstruction_loss: 10236.1631
```

Epoch 262/400
1/1 **0s** 226ms/step - kl_loss: 29.1650 - loss: 10247.6162
- reconstruction_loss: 10218.4512
Epoch 263/400
1/1 **0s** 221ms/step - kl_loss: 27.2356 - loss: 10245.9238
- reconstruction_loss: 10218.6885
Epoch 264/400
1/1 **0s** 233ms/step - kl_loss: 26.5268 - loss: 10266.7168
- reconstruction_loss: 10240.1904
Epoch 265/400
1/1 **0s** 246ms/step - kl_loss: 29.1959 - loss: 10228.6631
- reconstruction_loss: 10199.4668
Epoch 266/400
1/1 **0s** 217ms/step - kl_loss: 30.6520 - loss: 10243.8691
- reconstruction_loss: 10213.2168
Epoch 267/400
1/1 **0s** 229ms/step - kl_loss: 29.0617 - loss: 10233.6689
- reconstruction_loss: 10204.6074
Epoch 268/400
1/1 **0s** 224ms/step - kl_loss: 26.7848 - loss: 10230.4590
- reconstruction_loss: 10203.6738
Epoch 269/400
1/1 **0s** 233ms/step - kl_loss: 28.0701 - loss: 10218.6543
- reconstruction_loss: 10190.5840
Epoch 270/400
1/1 **0s** 247ms/step - kl_loss: 30.1480 - loss: 10219.8047
- reconstruction_loss: 10189.6562
Epoch 271/400
1/1 **0s** 219ms/step - kl_loss: 28.8695 - loss: 10209.2012
- reconstruction_loss: 10180.3320
Epoch 272/400
1/1 **0s** 207ms/step - kl_loss: 26.9777 - loss: 10192.6025
- reconstruction_loss: 10165.6250
Epoch 273/400
1/1 **0s** 208ms/step - kl_loss: 27.4101 - loss: 10186.9336
- reconstruction_loss: 10159.5234
Epoch 274/400
1/1 **0s** 207ms/step - kl_loss: 29.3490 - loss: 10185.5400
- reconstruction_loss: 10156.1914
Epoch 275/400
1/1 **0s** 208ms/step - kl_loss: 29.9305 - loss: 10193.2148
- reconstruction_loss: 10163.2842
Epoch 276/400
1/1 **0s** 209ms/step - kl_loss: 27.7822 - loss: 10174.7334
- reconstruction_loss: 10146.9512
Epoch 277/400
1/1 **0s** 208ms/step - kl_loss: 27.3527 - loss: 10191.2930
- reconstruction_loss: 10163.9404
Epoch 278/400
1/1 **0s** 210ms/step - kl_loss: 30.4174 - loss: 10196.4521
- reconstruction_loss: 10166.0352
Epoch 279/400
1/1 **0s** 208ms/step - kl_loss: 30.2434 - loss: 10159.4756
- reconstruction_loss: 10129.2324
Epoch 280/400
1/1 **0s** 206ms/step - kl_loss: 27.6868 - loss: 10195.7002

```
- reconstruction_loss: 10168.0137
Epoch 281/400
1/1 0s 207ms/step - kl_loss: 28.8181 - loss: 10143.1709
- reconstruction_loss: 10114.3525
Epoch 282/400
1/1 0s 215ms/step - kl_loss: 30.9144 - loss: 10163.8281
- reconstruction_loss: 10132.9141
Epoch 283/400
1/1 0s 209ms/step - kl_loss: 29.0115 - loss: 10126.8066
- reconstruction_loss: 10097.7949
Epoch 284/400
1/1 0s 210ms/step - kl_loss: 27.1828 - loss: 10125.1221
- reconstruction_loss: 10097.9395
Epoch 285/400
1/1 0s 207ms/step - kl_loss: 27.8153 - loss: 10143.7158
- reconstruction_loss: 10115.9004
Epoch 286/400
1/1 0s 217ms/step - kl_loss: 30.8616 - loss: 10134.4023
- reconstruction_loss: 10103.5410
Epoch 287/400
1/1 0s 211ms/step - kl_loss: 30.7325 - loss: 10132.1729
- reconstruction_loss: 10101.4404
Epoch 288/400
1/1 0s 209ms/step - kl_loss: 28.0838 - loss: 10119.7578
- reconstruction_loss: 10091.6738
Epoch 289/400
1/1 0s 207ms/step - kl_loss: 28.6062 - loss: 10096.8115
- reconstruction_loss: 10068.2051
Epoch 290/400
1/1 0s 212ms/step - kl_loss: 29.8231 - loss: 10092.9531
- reconstruction_loss: 10063.1299
Epoch 291/400
1/1 0s 210ms/step - kl_loss: 30.0932 - loss: 10093.5908
- reconstruction_loss: 10063.4980
Epoch 292/400
1/1 0s 212ms/step - kl_loss: 29.3590 - loss: 10088.2705
- reconstruction_loss: 10058.9111
Epoch 293/400
1/1 0s 211ms/step - kl_loss: 28.9713 - loss: 10099.6396
- reconstruction_loss: 10070.6680
Epoch 294/400
1/1 0s 211ms/step - kl_loss: 29.2326 - loss: 10084.8203
- reconstruction_loss: 10055.5879
Epoch 295/400
1/1 0s 211ms/step - kl_loss: 29.0122 - loss: 10066.1641
- reconstruction_loss: 10037.1523
Epoch 296/400
1/1 0s 208ms/step - kl_loss: 29.9733 - loss: 10050.9121
- reconstruction_loss: 10020.9385
Epoch 297/400
1/1 0s 212ms/step - kl_loss: 29.1141 - loss: 10062.6670
- reconstruction_loss: 10033.5527
Epoch 298/400
1/1 0s 209ms/step - kl_loss: 28.2968 - loss: 10043.4336
- reconstruction_loss: 10015.1367
Epoch 299/400
```

```
1/1 _____ 0s 209ms/step - kl_loss: 28.4649 - loss: 10056.3408
- reconstruction_loss: 10027.8760
Epoch 300/400
1/1 _____ 0s 210ms/step - kl_loss: 29.6942 - loss: 10035.0479
- reconstruction_loss: 10005.3535
Epoch 301/400
1/1 _____ 0s 207ms/step - kl_loss: 29.2043 - loss: 10039.5928
- reconstruction_loss: 10010.3887
Epoch 302/400
1/1 _____ 0s 206ms/step - kl_loss: 28.4217 - loss: 10029.6367
- reconstruction_loss: 10001.2148
Epoch 303/400
1/1 _____ 0s 208ms/step - kl_loss: 29.5507 - loss: 10015.6562
- reconstruction_loss: 9986.1055
Epoch 304/400
1/1 _____ 0s 213ms/step - kl_loss: 30.0469 - loss: 10018.2129
- reconstruction_loss: 9988.1660
Epoch 305/400
1/1 _____ 0s 207ms/step - kl_loss: 29.1071 - loss: 10019.0645
- reconstruction_loss: 9989.9570
Epoch 306/400
1/1 _____ 0s 220ms/step - kl_loss: 28.7208 - loss: 10018.2822
- reconstruction_loss: 9989.5615
Epoch 307/400
1/1 _____ 0s 211ms/step - kl_loss: 30.0985 - loss: 10013.0557
- reconstruction_loss: 9982.9570
Epoch 308/400
1/1 _____ 0s 208ms/step - kl_loss: 29.7327 - loss: 10002.2588
- reconstruction_loss: 9972.5264
Epoch 309/400
1/1 _____ 0s 209ms/step - kl_loss: 28.1505 - loss: 10022.8984
- reconstruction_loss: 9994.7480
Epoch 310/400
1/1 _____ 0s 217ms/step - kl_loss: 29.7901 - loss: 9993.8721
- reconstruction_loss: 9964.0820
Epoch 311/400
1/1 _____ 0s 210ms/step - kl_loss: 31.5331 - loss: 10021.5869
- reconstruction_loss: 9990.0537
Epoch 312/400
1/1 _____ 0s 210ms/step - kl_loss: 29.0827 - loss: 9986.2441
- reconstruction_loss: 9957.1611
Epoch 313/400
1/1 _____ 0s 212ms/step - kl_loss: 26.9408 - loss: 10020.0527
- reconstruction_loss: 9993.1123
Epoch 314/400
1/1 _____ 0s 211ms/step - kl_loss: 29.4414 - loss: 9975.3066
- reconstruction_loss: 9945.8652
Epoch 315/400
1/1 _____ 0s 208ms/step - kl_loss: 31.7649 - loss: 9998.5518
- reconstruction_loss: 9966.7871
Epoch 316/400
1/1 _____ 0s 208ms/step - kl_loss: 29.5231 - loss: 9973.2422
- reconstruction_loss: 9943.7188
Epoch 317/400
1/1 _____ 0s 219ms/step - kl_loss: 27.7324 - loss: 9982.5781
- reconstruction_loss: 9954.8457
```

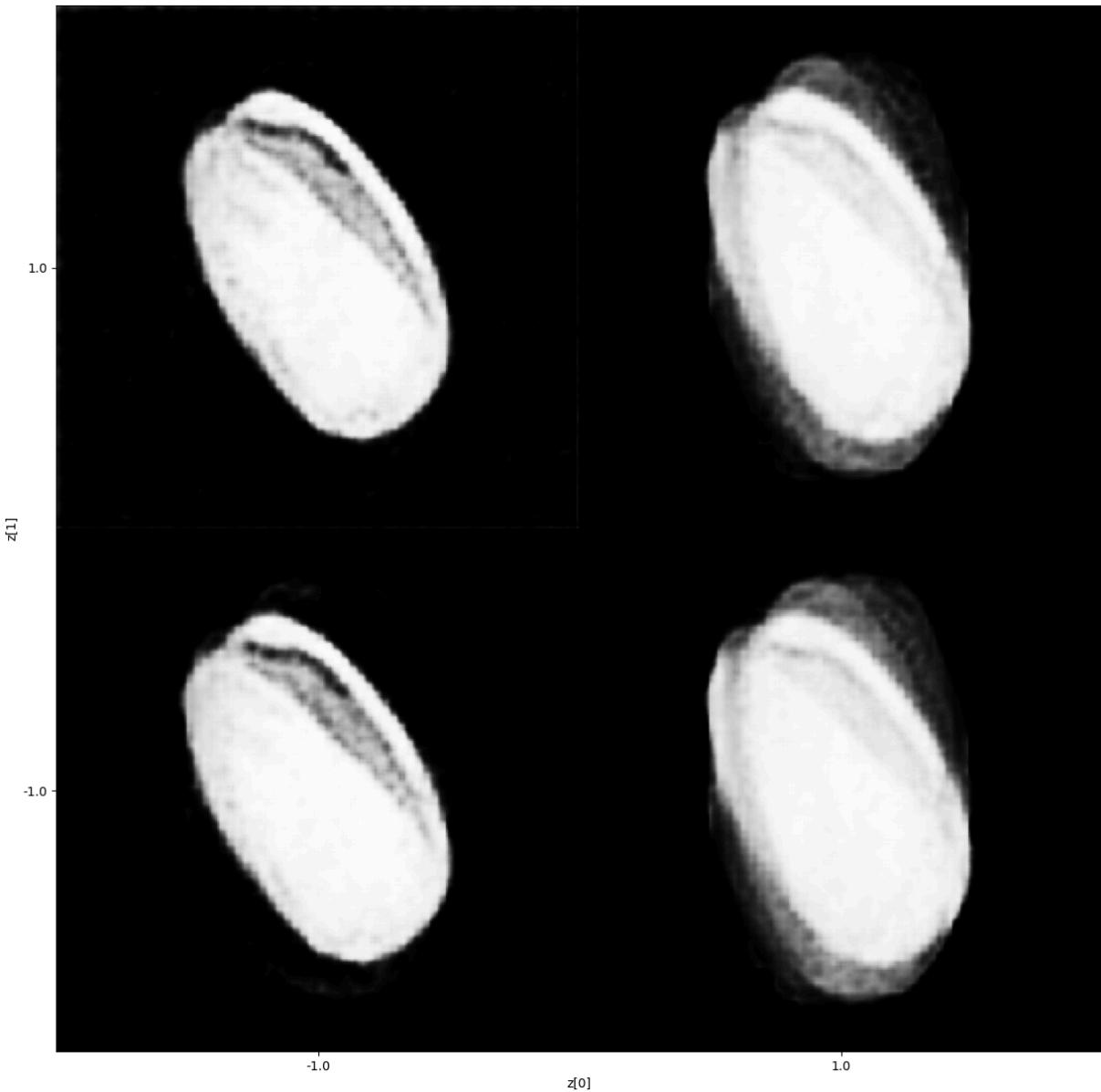
Epoch 318/400
1/1 **0s** 234ms/step - kl_loss: 29.9234 - loss: 9964.5781
- reconstruction_loss: 9934.6543
Epoch 319/400
1/1 **0s** 238ms/step - kl_loss: 31.0055 - loss: 9967.4844
- reconstruction_loss: 9936.4785
Epoch 320/400
1/1 **0s** 233ms/step - kl_loss: 29.2796 - loss: 9969.4980
- reconstruction_loss: 9940.2188
Epoch 321/400
1/1 **0s** 243ms/step - kl_loss: 29.2545 - loss: 9949.3955
- reconstruction_loss: 9920.1406
Epoch 322/400
1/1 **0s** 228ms/step - kl_loss: 29.2454 - loss: 9963.3896
- reconstruction_loss: 9934.1445
Epoch 323/400
1/1 **0s** 232ms/step - kl_loss: 30.6274 - loss: 9946.5977
- reconstruction_loss: 9915.9707
Epoch 324/400
1/1 **0s** 246ms/step - kl_loss: 29.7754 - loss: 9929.5625
- reconstruction_loss: 9899.7871
Epoch 325/400
1/1 **0s** 231ms/step - kl_loss: 28.1061 - loss: 9943.1104
- reconstruction_loss: 9915.0039
Epoch 326/400
1/1 **0s** 218ms/step - kl_loss: 29.1269 - loss: 9925.9551
- reconstruction_loss: 9896.8281
Epoch 327/400
1/1 **0s** 212ms/step - kl_loss: 30.7017 - loss: 9920.1504
- reconstruction_loss: 9889.4482
Epoch 328/400
1/1 **0s** 210ms/step - kl_loss: 30.0025 - loss: 9925.0322
- reconstruction_loss: 9895.0293
Epoch 329/400
1/1 **0s** 215ms/step - kl_loss: 29.3254 - loss: 9936.7920
- reconstruction_loss: 9907.4668
Epoch 330/400
1/1 **0s** 210ms/step - kl_loss: 32.0391 - loss: 9987.9453
- reconstruction_loss: 9955.9062
Epoch 331/400
1/1 **0s** 211ms/step - kl_loss: 29.3305 - loss: 9937.2207
- reconstruction_loss: 9907.8906
Epoch 332/400
1/1 **0s** 209ms/step - kl_loss: 26.7022 - loss: 9981.0010
- reconstruction_loss: 9954.2988
Epoch 333/400
1/1 **0s** 215ms/step - kl_loss: 29.6626 - loss: 9922.6221
- reconstruction_loss: 9892.9590
Epoch 334/400
1/1 **0s** 211ms/step - kl_loss: 31.9832 - loss: 9974.0420
- reconstruction_loss: 9942.0586
Epoch 335/400
1/1 **0s** 211ms/step - kl_loss: 28.6237 - loss: 9927.2988
- reconstruction_loss: 9898.6748
Epoch 336/400
1/1 **0s** 209ms/step - kl_loss: 26.6828 - loss: 9989.5469

```
- reconstruction_loss: 9962.8643
Epoch 337/400
1/1 0s 209ms/step - kl_loss: 30.4442 - loss: 9888.4502
- reconstruction_loss: 9858.0059
Epoch 338/400
1/1 0s 211ms/step - kl_loss: 33.1567 - loss: 9952.7773
- reconstruction_loss: 9919.6211
Epoch 339/400
1/1 0s 208ms/step - kl_loss: 29.8787 - loss: 9909.9297
- reconstruction_loss: 9880.0508
Epoch 340/400
1/1 0s 211ms/step - kl_loss: 28.3705 - loss: 9903.6396
- reconstruction_loss: 9875.2695
Epoch 341/400
1/1 0s 215ms/step - kl_loss: 30.5728 - loss: 9868.3252
- reconstruction_loss: 9837.7520
Epoch 342/400
1/1 0s 209ms/step - kl_loss: 32.7513 - loss: 9895.4922
- reconstruction_loss: 9862.7412
Epoch 343/400
1/1 0s 208ms/step - kl_loss: 30.5325 - loss: 9870.3662
- reconstruction_loss: 9839.8340
Epoch 344/400
1/1 0s 211ms/step - kl_loss: 28.9010 - loss: 9929.7988
- reconstruction_loss: 9900.8975
Epoch 345/400
1/1 0s 207ms/step - kl_loss: 31.9568 - loss: 9874.7100
- reconstruction_loss: 9842.7529
Epoch 346/400
1/1 0s 210ms/step - kl_loss: 31.5338 - loss: 9839.3291
- reconstruction_loss: 9807.7949
Epoch 347/400
1/1 0s 213ms/step - kl_loss: 29.1073 - loss: 9874.2051
- reconstruction_loss: 9845.0977
Epoch 348/400
1/1 0s 206ms/step - kl_loss: 30.4002 - loss: 9866.9756
- reconstruction_loss: 9836.5752
Epoch 349/400
1/1 0s 209ms/step - kl_loss: 29.4144 - loss: 9872.7969
- reconstruction_loss: 9843.3828
Epoch 350/400
1/1 0s 210ms/step - kl_loss: 27.6860 - loss: 9883.5537
- reconstruction_loss: 9855.8682
Epoch 351/400
1/1 0s 210ms/step - kl_loss: 28.1355 - loss: 9850.9580
- reconstruction_loss: 9822.8223
Epoch 352/400
1/1 0s 208ms/step - kl_loss: 31.2515 - loss: 9876.9893
- reconstruction_loss: 9845.7373
Epoch 353/400
1/1 0s 212ms/step - kl_loss: 30.5283 - loss: 9837.3770
- reconstruction_loss: 9806.8486
Epoch 354/400
1/1 0s 210ms/step - kl_loss: 28.5681 - loss: 9843.7891
- reconstruction_loss: 9815.2207
Epoch 355/400
```

```
1/1 _____ 0s 212ms/step - kl_loss: 29.7131 - loss: 9832.0938
- reconstruction_loss: 9802.3809
Epoch 356/400
1/1 _____ 0s 214ms/step - kl_loss: 32.6354 - loss: 9890.3975
- reconstruction_loss: 9857.7617
Epoch 357/400
1/1 _____ 0s 222ms/step - kl_loss: 31.4578 - loss: 9813.0820
- reconstruction_loss: 9781.6240
Epoch 358/400
1/1 _____ 0s 218ms/step - kl_loss: 28.6119 - loss: 9824.9287
- reconstruction_loss: 9796.3164
Epoch 359/400
1/1 _____ 0s 209ms/step - kl_loss: 30.9683 - loss: 9787.5742
- reconstruction_loss: 9756.6055
Epoch 360/400
1/1 _____ 0s 206ms/step - kl_loss: 31.5368 - loss: 9784.8711
- reconstruction_loss: 9753.3340
Epoch 361/400
1/1 _____ 0s 210ms/step - kl_loss: 29.4753 - loss: 9780.1240
- reconstruction_loss: 9750.6484
Epoch 362/400
1/1 _____ 0s 211ms/step - kl_loss: 29.9684 - loss: 9748.5771
- reconstruction_loss: 9718.6084
Epoch 363/400
1/1 _____ 0s 209ms/step - kl_loss: 33.2968 - loss: 9950.7354
- reconstruction_loss: 9917.4385
Epoch 364/400
1/1 _____ 0s 211ms/step - kl_loss: 36.6525 - loss: 10173.5430
- reconstruction_loss: 10136.8906
Epoch 365/400
1/1 _____ 0s 211ms/step - kl_loss: 27.1831 - loss: 9911.4424
- reconstruction_loss: 9884.2598
Epoch 366/400
1/1 _____ 0s 215ms/step - kl_loss: 21.4308 - loss: 10121.9951
- reconstruction_loss: 10100.5645
Epoch 367/400
1/1 _____ 0s 210ms/step - kl_loss: 25.3718 - loss: 9869.3643
- reconstruction_loss: 9843.9922
Epoch 368/400
1/1 _____ 0s 214ms/step - kl_loss: 32.8924 - loss: 10083.3887
- reconstruction_loss: 10050.4961
Epoch 369/400
1/1 _____ 0s 213ms/step - kl_loss: 29.6875 - loss: 9862.0625
- reconstruction_loss: 9832.3750
Epoch 370/400
1/1 _____ 0s 210ms/step - kl_loss: 25.4025 - loss: 9974.0801
- reconstruction_loss: 9948.6777
Epoch 371/400
1/1 _____ 0s 215ms/step - kl_loss: 27.3407 - loss: 9859.6377
- reconstruction_loss: 9832.2969
Epoch 372/400
1/1 _____ 0s 210ms/step - kl_loss: 33.0467 - loss: 9874.3203
- reconstruction_loss: 9841.2734
Epoch 373/400
1/1 _____ 0s 224ms/step - kl_loss: 33.8422 - loss: 9879.5938
- reconstruction_loss: 9845.7520
```

Epoch 374/400
1/1 **0s** 228ms/step - kl_loss: 29.5080 - loss: 9779.9355
- reconstruction_loss: 9750.4277
Epoch 375/400
1/1 **0s** 228ms/step - kl_loss: 27.6857 - loss: 9807.6543
- reconstruction_loss: 9779.9688
Epoch 376/400
1/1 **0s** 235ms/step - kl_loss: 29.8327 - loss: 9768.8682
- reconstruction_loss: 9739.0352
Epoch 377/400
1/1 **0s** 234ms/step - kl_loss: 32.8392 - loss: 9814.7334
- reconstruction_loss: 9781.8945
Epoch 378/400
1/1 **0s** 243ms/step - kl_loss: 30.1969 - loss: 9731.7988
- reconstruction_loss: 9701.6016
Epoch 379/400
1/1 **0s** 247ms/step - kl_loss: 27.5358 - loss: 9749.4102
- reconstruction_loss: 9721.8740
Epoch 380/400
1/1 **0s** 248ms/step - kl_loss: 28.0085 - loss: 9688.0225
- reconstruction_loss: 9660.0137
Epoch 381/400
1/1 **0s** 246ms/step - kl_loss: 30.3126 - loss: 9683.4111
- reconstruction_loss: 9653.0986
Epoch 382/400
1/1 **0s** 211ms/step - kl_loss: 31.5790 - loss: 9702.0293
- reconstruction_loss: 9670.4502
Epoch 383/400
1/1 **0s** 211ms/step - kl_loss: 29.7985 - loss: 9668.3848
- reconstruction_loss: 9638.5859
Epoch 384/400
1/1 **0s** 211ms/step - kl_loss: 28.6725 - loss: 9666.6201
- reconstruction_loss: 9637.9473
Epoch 385/400
1/1 **0s** 209ms/step - kl_loss: 30.5375 - loss: 9617.6465
- reconstruction_loss: 9587.1094
Epoch 386/400
1/1 **0s** 210ms/step - kl_loss: 32.2173 - loss: 9645.6338
- reconstruction_loss: 9613.4160
Epoch 387/400
1/1 **0s** 212ms/step - kl_loss: 31.7533 - loss: 9636.1768
- reconstruction_loss: 9604.4238
Epoch 388/400
1/1 **0s** 211ms/step - kl_loss: 29.5847 - loss: 9638.1680
- reconstruction_loss: 9608.5830
Epoch 389/400
1/1 **0s** 215ms/step - kl_loss: 28.8376 - loss: 9649.9902
- reconstruction_loss: 9621.1523
Epoch 390/400
1/1 **0s** 214ms/step - kl_loss: 30.4667 - loss: 9634.9570
- reconstruction_loss: 9604.4902
Epoch 391/400
1/1 **0s** 212ms/step - kl_loss: 32.4023 - loss: 9605.2109
- reconstruction_loss: 9572.8086
Epoch 392/400
1/1 **0s** 209ms/step - kl_loss: 31.6850 - loss: 9589.6445

```
- reconstruction_loss: 9557.9600
Epoch 393/400
1/1 0s 213ms/step - kl_loss: 30.1174 - loss: 9590.2109
- reconstruction_loss: 9560.0938
Epoch 394/400
1/1 0s 211ms/step - kl_loss: 29.2665 - loss: 9610.4062
- reconstruction_loss: 9581.1396
Epoch 395/400
1/1 0s 209ms/step - kl_loss: 31.0020 - loss: 9576.6934
- reconstruction_loss: 9545.6914
Epoch 396/400
1/1 0s 211ms/step - kl_loss: 31.1920 - loss: 9583.5332
- reconstruction_loss: 9552.3408
Epoch 397/400
1/1 0s 213ms/step - kl_loss: 29.2836 - loss: 9575.0039
- reconstruction_loss: 9545.7207
Epoch 398/400
1/1 0s 211ms/step - kl_loss: 28.9545 - loss: 9586.3877
- reconstruction_loss: 9557.4336
Epoch 399/400
1/1 0s 208ms/step - kl_loss: 29.9523 - loss: 9641.2314
- reconstruction_loss: 9611.2793
Epoch 400/400
1/1 0s 219ms/step - kl_loss: 32.3025 - loss: 9672.1367
- reconstruction_loss: 9639.8340
Plotting latent space...
```



FINAL INSIGHTS THE MODEL SUCCESSFUL IN RECONSTRUCTING THE PISTACHIO IMAGE WITH GOOD ACCURACY

IMPROVEMENTS CAN BE DONE

DATA AUGMENTATION LIKE RANDOM FLIP, RANDOM ROTATION, RANDOM CROP CAN IMPROVE THE ACCURACY AND AVOID OVERFITTING

IT CAN BE TRAINED ON 500 TO 700 EPOCHS FOR BETTER IMAGE GENERATION

SCOPE IN MARKET

VAN CAN BE USED TO GENERATE SYNTHETIC IMAGE DATA WHICH CAN IMPROVE THE LOW DATA PROBLEM

IT CAN UPSCALE THE IMAGE IT CAN BE DEPLOYED IN AI THAT CAN UPSCALE THE IMAGE FROM LOW RESOLUTION TO HIGH RESOLUTION

IT CAN BE USED TO RESTORE DAMAGED IMAGES AND RECREATE THE DAMAGE AREA

IT CAN BE DEPLOYED AS WATERMARK REMOVE AND CAN REMOVE THE WATERMARK ON PHOTOS

FLAWS

MODEL LIKE VAN SMOOTH OUT IMAGES MEANS THE IMAGE IS NOT AS SHARP AS ORIGINAL

MODEL ONLY GENERATE IMAGES ON WHICH IT IS TRAINED

MODEL CAN SUFFER FROM OVERRFITTING BUT NOT AS MUCH AS AUTOENCODER

IT REQUIRE HUGE COMPUTATIONAL POWER TO TRAIN THIS MODEL