세상에 없는 얼굴 GAN, 오토인코더

3. 적대적 신경망 실행하기

실습: GAN 모델 만들기

```
In [4]: from tensorflow.keras.datasets import mnist
        from tensorflow.keras.layers import Input, Dense, Reshape, Flatten, Dropout
        from tensorflow.keras.layers import BatchNormalization, Activation, LeakyReLU, UpSampling2D, Conv2D
        from tensorflow.keras.models import Sequential, Model
        import numpy as np
        import matplotlib.pyplot as plt
        # 생성자 모델을 만듭니다.
        generator = Sequential()
        generator.add(Dense(128*7*7, input dim=100, activation=LeakyReLU(0.2)))
        generator.add(BatchNormalization())
        generator.add(Reshape((7, 7, 128)))
        generator.add(UpSampling2D())
        generator.add(Conv2D(64, kernel size=5, padding='same'))
        generator.add(BatchNormalization())
        generator.add(Activation(LeakyReLU(0.2)))
        generator.add(UpSampling2D())
        generator.add(Conv2D(1, kernel_size=5, padding='same', activation='tanh'))
        # 판별자 모델을 만듭니다.
        discriminator = Sequential()
        discriminator.add(Conv2D(64, kernel_size=5, strides=2, input_shape=(28,28,1), padding="same"))
        discriminator.add(Activation(LeakyReLU(0.2)))
        discriminator.add(Dropout(0.3))
        discriminator.add(Conv2D(128, kernel size=5, strides=2, padding="same"))
        discriminator.add(Activation(LeakyReLU(0.2)))
        discriminator.add(Dropout(0.3))
```

```
discriminator.add(Flatten())
discriminator.add(Dense(1, activation='sigmoid'))
discriminator.compile(loss='binary crossentropy', optimizer='adam')
discriminator.trainable = False
# 생성자와 판별자 모델을 연결시키는 qan 모델을 만듭니다.
ginput = Input(shape=(100,))
dis output = discriminator(generator(ginput))
gan = Model(ginput, dis output)
gan.compile(loss='binary crossentropy', optimizer='adam')
gan.summary()
# 신경망을 실행시키는 함수를 만듭니다.
def gan train(epoch, batch size, saving interval):
 # MNIST 데이터를 불러옵니다.
 (X train, ), ( , ) = mnist.load data() # 앞서 불러온 적 있는 MNIST를 다시 이용합니다.
 #단, 테스트 과정은 필요 없고 이미지만 사용할 것이기 때문에 X train만 불러왔습니다.
 X train = X train.reshape(X_train.shape[0], 28, 28, 1).astype('float32')
 X train = (X train - 127.5) / 127.5 # 픽셀 값은 0에서 255 사이의 값입니다.
 #이전에 255로 나누어 줄때는 이를 0~1 사이의 값으로 바꾸었던 것인데,
 #여기서는 127.5를 빼준 뒤 127.5로 나누어 줌으로 인해 -1에서 1사이의 값으로 바뀌게 됩니다.
 # X train.shape, Y train.shape, X test.shape, Y test.shape
 true = np.ones((batch size, 1))
 fake = np.zeros((batch size, 1))
 for i in range(epoch):
        # 실제 데이터를 판별자에 입력하는 부분입니다.
        idx = np.random.randint(0, X train.shape[0], batch size)
        imgs = X train[idx]
        d loss real = discriminator.train on batch(imgs, true)
        # 가상 이미지를 판별자에 입력하는 부분입니다.
        noise = np.random.normal(0, 1, (batch size, 100))
        gen imgs = generator.predict(noise, verbose=0)
        d loss fake = discriminator.train on batch(gen imgs, fake)
        # 판별자와 생성자의 오차를 계산합니다.
        d loss = 0.5 * np.add(d loss real, d loss fake)
```

```
g loss = gan.train on batch(noise, true)
         if i % 100 == 0:
            print('epoch:%d' % i, ' d loss:%.4f' % d loss, ' g loss:%.4f' % g loss)
       # 이 부분은 중간 과정을 이미지로 저장해 주는 부분입니다. 이 장의 주요 내용과 관련이 없어
       # 소스 코드만 첨부합니다. 만들어진 이미지들은 qan images 폴더에 저장됩니다.
         if i % saving interval == 0:
            \#r, c = 5, 5
            noise = np.random.normal(0, 1, (25, 100))
            gen imgs = generator.predict(noise)
            # Rescale images 0 - 1
            gen imgs = 0.5 * gen imgs + 0.5
            fig, axs = plt.subplots(5, 5)
            count = 0
            for j in range(5):
                for k in range(5):
                   axs[j, k].imshow(gen imgs[count, :, :, 0], cmap='gray')
                   axs[j, k].axis('off')
                   count += 1
            fig.savefig("./gan mnist %d.png" % i)
gan_train(2001, 32, 200) # 2000번 반복되고, 배치 사이즈는 32, 200번마다 결과가 저장되게 하였습니다.
```

C:\Users\user\AppData\Roaming\Python\Python312\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an `in put_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first la yer in the model instead.

super().__init__(activity_regularizer=activity_regularizer, **kwargs)

C:\Users\user\AppData\Roaming\Python\Python312\site-packages\keras\src\layers\convolutional\base_conv.py:107: UserWarning: Do n ot pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object a s the first layer in the model instead.

super().__init__(activity_regularizer=activity_regularizer, **kwargs)

Model: "functional_17"

Layer (type)	Output Shape	Param #
<pre>input_layer_2 (InputLayer)</pre>	(None, 100)	0
sequential (Sequential)	(None, 28, 28, 1)	865,281
sequential_1 (Sequential)	(None, 1)	212,865

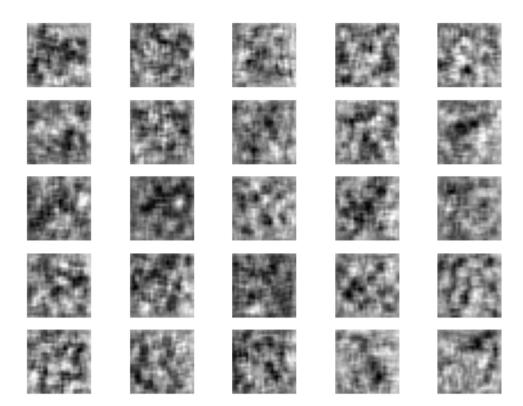
Total params: 1,078,146 (4.11 MB)
Trainable params: 852,609 (3.25 MB)

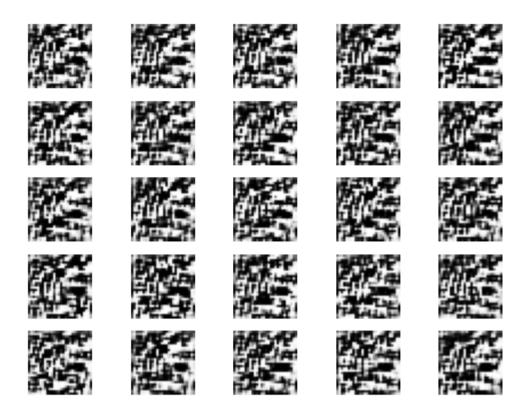
Non-trainable params: 225,537 (881.00 KB)

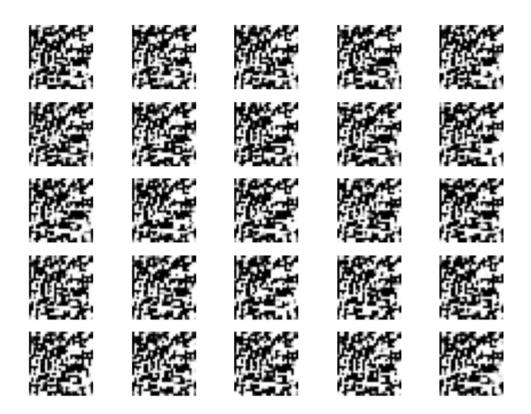
C:\Users\user\AppData\Roaming\Python\Python312\site-packages\keras\src\backend\tensorflow\trainer.py:82: UserWarning: The model
does not have any trainable weights.

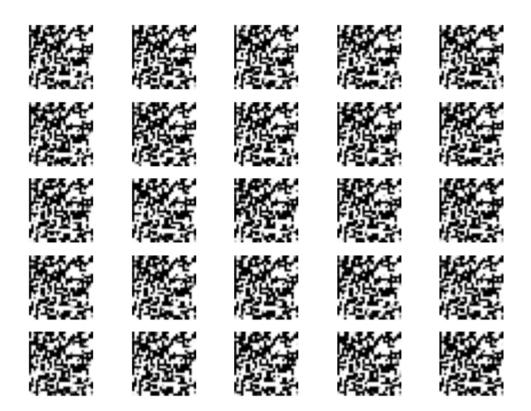
warnings.warn("The model does not have any trainable weights.")

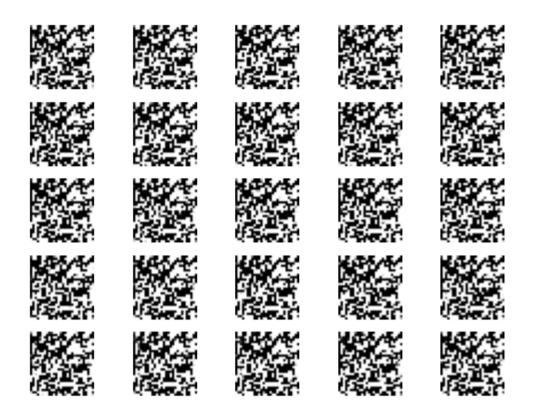
```
epoch:0 d loss:0.6919 g loss:0.6950
1/1 0s 122ms/step
epoch:100 d loss:0.7522 g loss:0.5738
epoch:200 d loss:0.8225 g loss:0.4942
1/1 ---
                     — 0s 28ms/step
epoch:300 d loss:0.8872 g loss:0.4327
epoch:400 d loss:0.9380 g loss:0.3897
                     — 0s 36ms/step
1/1 -
epoch:500 d loss:0.9779 g loss:0.3581
epoch:600 d loss:1.0103 g loss:0.3339
1/1 ---
                    — 0s 59ms/step
epoch:700 d loss:1.0364 g loss:0.3151
epoch:800 d loss:1.0584 g loss:0.2999
1/1 -
                     - 0s 30ms/step
epoch:900 d loss:1.0764 g loss:0.2876
epoch:1000 d loss:1.0914 g loss:0.2776
1/1 -
               Os 40ms/step
epoch:1100 d loss:1.1041 g loss:0.2692
epoch:1200 d loss:1.1148 g loss:0.2621
1/1 -
                    — 0s 38ms/step
epoch:1300 d loss:1.1242 g loss:0.2561
epoch:1400 d loss:1.1323 g loss:0.2508
           0s 30ms/step
1/1 -
epoch:1500 d loss:1.1393 g loss:0.2463
epoch:1600 d loss:1.1454 g loss:0.2424
1/1 -
                      - 0s 29ms/step
epoch:1700 d loss:1.1510 g loss:0.2388
epoch:1800 d loss:1.1560 g_loss:0.2357
                     - 0s 28ms/step
1/1 ---
epoch:1900 d loss:1.1603 g loss:0.2329
epoch:2000 d loss:1.1644 g loss:0.2303
1/1 ---
                      - 0s 29ms/step
```

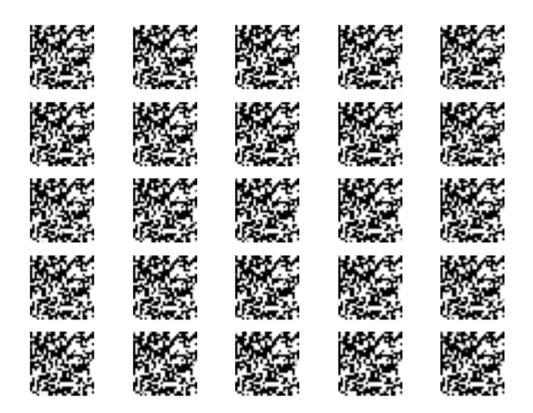


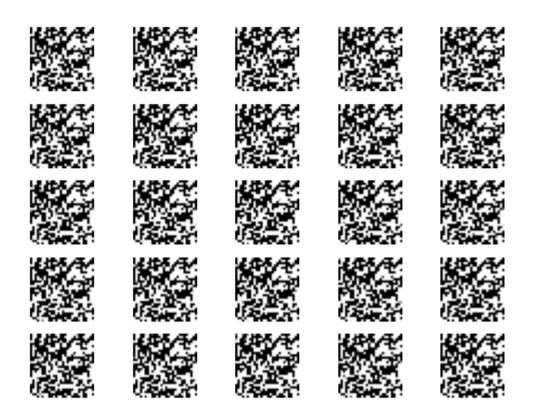


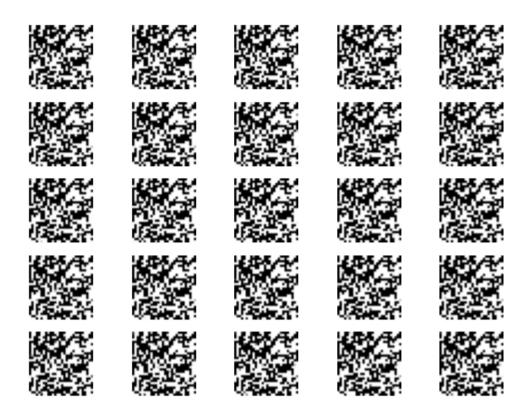


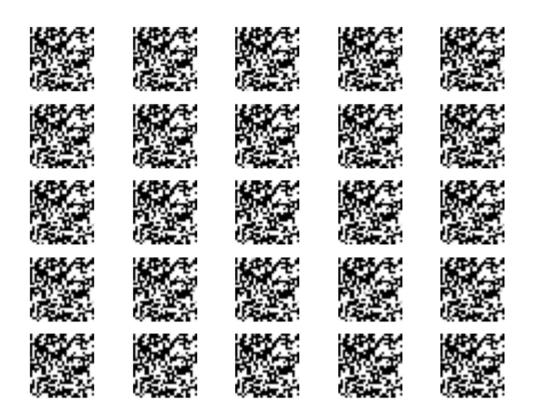


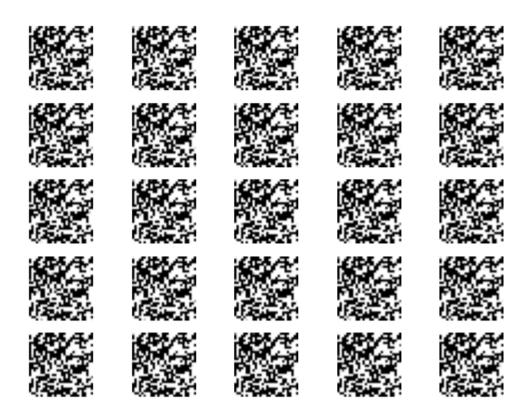


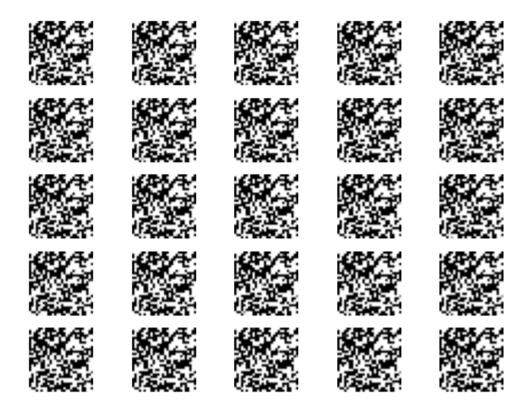












4. 이미지의 특징을 추출하는 오토인코더

실습: 오토인코더 실습하기

```
In [7]: from tensorflow.keras.datasets import mnist from tensorflow.keras.models import Sequential, Model from tensorflow.keras.layers import Input, Dense, Conv2D, MaxPooling2D, UpSampling2D, Flatten, Reshape import matplotlib.pyplot as plt import numpy as np
# MNIST 데이터셋을 불러옵니다.

(X_train, _), (X_test, _) = mnist.load_data()
```

```
X train = X train.reshape(X train.shape[0], 28, 28, 1).astype('float32') / 255
X test = X test.reshape(X test.shape[0], 28, 28, 1).astype('float32') / 255
# 생성자 모델을 만듭니다.
autoencoder = Sequential()
# 인코딩 부분입니다.
autoencoder.add(Conv2D(16, kernel size=3, padding='same', input shape=(28,28,1), activation='relu'))
autoencoder.add(MaxPooling2D(pool size=2, padding='same'))
autoencoder.add(Conv2D(8, kernel size=3, activation='relu', padding='same'))
autoencoder.add(MaxPooling2D(pool size=2, padding='same'))
autoencoder.add(Conv2D(8, kernel size=3, strides=2, padding='same', activation='relu'))
# 디코딩 부분입니다.
autoencoder.add(Conv2D(8, kernel size=3, padding='same', activation='relu'))
autoencoder.add(UpSampling2D())
autoencoder.add(Conv2D(8, kernel size=3, padding='same', activation='relu'))
autoencoder.add(UpSampling2D())
autoencoder.add(Conv2D(16, kernel size=3, activation='relu'))
autoencoder.add(UpSampling2D())
autoencoder.add(Conv2D(1, kernel size=3, padding='same', activation='sigmoid'))
# 전체 구조를 확인합니다.
autoencoder.summary()
```

Model: "sequential 2"

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 28, 28, 16)	160
max_pooling2d (MaxPooling2D)	(None, 14, 14, 16)	0
conv2d_5 (Conv2D)	(None, 14, 14, 8)	1,160
max_pooling2d_1 (MaxPooling2D)	(None, 7, 7, 8)	0
conv2d_6 (Conv2D)	(None, 4, 4, 8)	584
conv2d_7 (Conv2D)	(None, 4, 4, 8)	584
up_sampling2d_2 (UpSampling2D)	(None, 8, 8, 8)	0
conv2d_8 (Conv2D)	(None, 8, 8, 8)	584
up_sampling2d_3 (UpSampling2D)	(None, 16, 16, 8)	0
conv2d_9 (Conv2D)	(None, 14, 14, 16)	1,168
up_sampling2d_4 (UpSampling2D)	(None, 28, 28, 16)	0
conv2d_10 (Conv2D)	(None, 28, 28, 1)	145

Total params: 4,385 (17.13 KB)

Trainable params: 4,385 (17.13 KB)

Non-trainable params: 0 (0.00 B)

```
In [8]: # 컴파일 및 학습을 하는 부분입니다.
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
autoencoder.fit(X_train, X_train, epochs=50, batch_size=128, validation_data=(X_test, X_test))

# 학습된 결과를 출력하는 부분입니다.
random_test = np.random.randint(X_test.shape[0], size=5) # 테스트할 이미지를 랜덤하게 불러옵니다.
ae_imgs = autoencoder.predict(X_test) # 앞서 만든 오토인코더 모델에 집어 넣습니다.
```

```
plt.figure(figsize=(7, 2)) # 출력될 이미지의 크기를 정합니다.

for i, image_idx in enumerate(random_test): # 랜덤하게 뽑은 이미지를 차례로 나열합니다.
    ax = plt.subplot(2, 7, i + 1)
    plt.imshow(X_test[image_idx].reshape(28, 28)) # 테스트할 이미지를 먼저 그대로 보여줍니다.
    ax.axis('off')
    ax = plt.subplot(2, 7, 7 + i + 1)
    plt.imshow(ae_imgs[image_idx].reshape(28, 28)) # 오토인코딩 결과를 다음열에 출력합니다.
    ax.axis('off')
plt.show()
```

Epoch 1/50								
469/469	5s	8ms/step	-	loss:	0.3217	-	<pre>val_loss:</pre>	0.1399
Epoch 2/50								
	4s	8ms/step	-	loss:	0.1342	-	val_loss:	0.1197
Epoch 3/50								
469/469	4s	8ms/step	-	loss:	0.1176	-	val_loss:	0.1100
Epoch 4/50								
469/469	4s	8ms/step	-	loss:	0.1095	-	val_loss:	0.1048
Epoch 5/50								
469/469	4s	8ms/step	-	loss:	0.1049	-	val_loss:	0.1013
Epoch 6/50								
469/469	4 s	8ms/step	-	loss:	0.1017	-	val_loss:	0.0987
Epoch 7/50								
469/469	4 s	8ms/step	-	loss:	0.0995	-	val_loss:	0.0970
Epoch 8/50								
469/469	4s	8ms/step	-	loss:	0.0980	-	val_loss:	0.0962
Epoch 9/50								
469/469	4s	8ms/step	-	loss:	0.0966	-	val_loss:	0.0945
Epoch 10/50								
469/469	4s	7ms/step	-	loss:	0.0955	-	val_loss:	0.0935
Epoch 11/50								
469/469	4s	8ms/step	-	loss:	0.0946	-	val_loss:	0.0926
Epoch 12/50								
469/469	4s	8ms/step	-	loss:	0.0937	-	val_loss:	0.0919
Epoch 13/50				_				
469/469	4 s	8ms/step	-	loss:	0.0930	-	val_loss:	0.0911
Epoch 14/50	_			_				
	4s	8ms/step	-	loss:	0.0921	-	val_loss:	0.0905
Epoch 15/50	_							
	4s	8ms/step	-	loss:	0.0915	-	val_loss:	0.0900
Epoch 16/50								
469/469	45	8ms/step	-	loss:	0.0911	-	val_loss:	0.0893
Epoch 17/50	4 -	0 / - +		1	0.0006			0 0007
	45	8ms/step	-	1055:	0.0906	-	val_loss:	0.0887
Epoch 18/50	4 -	0 / - +		1	0.0000		1	0 0005
	45	8ms/step	-	1088:	0.0900	-	val_loss:	0.0885
Epoch 19/50	4	0		1	0.000		1	0 0070
469/469 ————————————————————————————————————	45	8ms/step	-	1088:	0.0892	-	val_loss:	0.0878
Epoch 20/50	4.	Omc / c+ a=		1055:	0 0000		val lass:	0 0072
469/469 ————————————————————————————————————	45	oms/step	-	1022:	9,0886	-	val_loss:	0.08/2
Epoch 21/50								

Epoch 22/50 469/469	469/469	4s	7ms/step	-	loss:	0.0882	-	val_loss:	0.0869
Epoch 23/50 469/469									
45 8ms/step - loss: 0.0875 - val_loss: 0.0864		4s	8ms/step	-	loss:	0.0880	-	val_loss:	0.0865
Epoch 24/50 469/469	•								
## 45 ## 8 ## 5 ## 5 ## 5 ## 5 ## 5 ## 5		4s	8ms/step	-	loss:	0.0875	-	val_loss:	0.0864
Epoch 25/50 469/469									
45 45 45 45 45 45 469 45 45 469 45 45 469 469 45 45 469	469/469	4s	8ms/step	-	loss:	0.0872	-	val_loss:	0.0858
Epoch 26/50 469/469									
## 45 8ms/step - loss: 0.0862 - val_loss: 0.0850	469/469	4s	8ms/step	-	loss:	0.0867	-	<pre>val_loss:</pre>	0.0857
Epoch 27/50 469/469									
## 45 8ms/step - loss: 0.0860 - val_loss: 0.0848 Epoch 28/50 ### 45 8ms/step - loss: 0.0855 - val_loss: 0.0846 Epoch 29/50 ### 45 8ms/step - loss: 0.0855 - val_loss: 0.0846 Epoch 30/50 ### 45 8ms/step - loss: 0.0855 - val_loss: 0.0843 Epoch 30/50 ### 469/469	469/469	4s	8ms/step	-	loss:	0.0862	-	<pre>val_loss:</pre>	0.0850
## ## ## ## ## ## ## ## ## ## ## ## ##									
469/469 4s 8ms/step - loss: 0.0855 - val_loss: 0.0846 Epoch 29/50 469/469 4s 8ms/step - loss: 0.0855 - val_loss: 0.0843 Epoch 30/50 469/469 4s 8ms/step - loss: 0.0854 - val_loss: 0.0840 Epoch 31/50 469/469 4s 8ms/step - loss: 0.0849 - val_loss: 0.0842 Epoch 32/50 469/469 4s 8ms/step - loss: 0.0849 - val_loss: 0.0837 Epoch 33/50 469/469 4s 8ms/step - loss: 0.0846 - val_loss: 0.0834 Epoch 34/50 469/469 4s 8ms/step - loss: 0.0846 - val_loss: 0.0832 Epoch 35/50 469/469 4s 8ms/step - loss: 0.0842 - val_loss: 0.0830 Epoch 36/50 469/469 4s 8ms/step - loss: 0.0841 - val_loss: 0.0829 Epoch 37/50 469/469 4s 8ms/step - loss: 0.0840 - val_loss: 0.0828 Epoch 38/50 469/469 4s 8ms/step - loss: 0.0839 - val_loss: 0.0825 Epoch 39/50 469/469 4s 8ms/step - loss: 0.0837 - val_loss: 0.0825 Epoch 40/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 40/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823	469/469	4s	8ms/step	-	loss:	0.0860	-	<pre>val_loss:</pre>	0.0848
## ## ## ## ## ## ## ## ## ## ## ## ##									
### 469/469 ### 45 8ms/step - loss: 0.0855 - val_loss: 0.0843 Epoch 30/50 #### 469/469 ### 45 8ms/step - loss: 0.0854 - val_loss: 0.0840 Epoch 31/50 #### 469/469 ### 45 8ms/step - loss: 0.0849 - val_loss: 0.0842 Epoch 32/50 #### 469/469 ### 45 8ms/step - loss: 0.0849 - val_loss: 0.0837 Epoch 33/50 #### 469/469 ### 45 8ms/step - loss: 0.0846 - val_loss: 0.0834 Epoch 34/50 #### 469/469 ### 45 8ms/step - loss: 0.0846 - val_loss: 0.0830 Epoch 36/50 #### 469/469 ### 45 8ms/step - loss: 0.0841 - val_loss: 0.0829 Epoch 37/50 ##### 469/469 ### 45 8ms/step - loss: 0.0840 - val_loss: 0.0828 Epoch 38/50 ####################################	469/469	4s	8ms/step	-	loss:	0.0855	-	<pre>val_loss:</pre>	0.0846
Epoch 30/50 469/469	•								
469/469 4s 8ms/step - loss: 0.0854 - val_loss: 0.0840 Epoch 31/50 469/469 4s 8ms/step - loss: 0.0849 - val_loss: 0.0842 Epoch 32/50 469/469 4s 8ms/step - loss: 0.0849 - val_loss: 0.0837 Epoch 33/50 469/469 4s 8ms/step - loss: 0.0846 - val_loss: 0.0834 Epoch 34/50 469/469 4s 8ms/step - loss: 0.0846 - val_loss: 0.0832 Epoch 35/50 469/469 4s 8ms/step - loss: 0.0842 - val_loss: 0.0830 Epoch 36/50 469/469 4s 8ms/step - loss: 0.0841 - val_loss: 0.0829 Epoch 37/50 469/469 4s 8ms/step - loss: 0.0840 - val_loss: 0.0828 Epoch 38/50 469/469 4s 8ms/step - loss: 0.0839 - val_loss: 0.0825 Epoch 39/50 469/469 4s 8ms/step - loss: 0.0837 - val_loss: 0.0825 Epoch 40/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 40/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823	469/469	4s	8ms/step	-	loss:	0.0855	-	<pre>val_loss:</pre>	0.0843
Epoch 31/50 469/469 — 4s 8ms/step - loss: 0.0849 - val_loss: 0.0842 Epoch 32/50 469/469 — 4s 8ms/step - loss: 0.0849 - val_loss: 0.0837 Epoch 33/50 469/469 — 4s 8ms/step - loss: 0.0846 - val_loss: 0.0834 Epoch 34/50 469/469 — 4s 8ms/step - loss: 0.0846 - val_loss: 0.0832 Epoch 35/50 469/469 — 4s 8ms/step - loss: 0.0842 - val_loss: 0.0830 Epoch 36/50 469/469 — 4s 8ms/step - loss: 0.0841 - val_loss: 0.0829 Epoch 37/50 469/469 — 4s 8ms/step - loss: 0.0840 - val_loss: 0.0828 Epoch 38/50 469/469 — 4s 8ms/step - loss: 0.0839 - val_loss: 0.0825 Epoch 39/50 469/469 — 4s 8ms/step - loss: 0.0837 - val_loss: 0.0825 Epoch 40/50 469/469 — 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 41/50	Epoch 30/50								
469/469 4s 8ms/step - loss: 0.0849 - val_loss: 0.0842 Epoch 32/50 469/469 4s 8ms/step - loss: 0.0849 - val_loss: 0.0837 Epoch 33/50 469/469 4s 8ms/step - loss: 0.0846 - val_loss: 0.0834 Epoch 34/50 469/469 4s 8ms/step - loss: 0.0846 - val_loss: 0.0832 Epoch 35/50 469/469 4s 8ms/step - loss: 0.0842 - val_loss: 0.0830 Epoch 36/50 469/469 4s 8ms/step - loss: 0.0841 - val_loss: 0.0829 Epoch 37/50 469/469 4s 8ms/step - loss: 0.0840 - val_loss: 0.0828 Epoch 38/50 469/469 4s 8ms/step - loss: 0.0839 - val_loss: 0.0825 Epoch 39/50 469/469 4s 8ms/step - loss: 0.0837 - val_loss: 0.0825 Epoch 40/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 41/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823	469/469	4s	8ms/step	-	loss:	0.0854	-	<pre>val_loss:</pre>	0.0840
Epoch 32/50 469/469									
469/4694s8ms/step - loss: 0.0849 - val_loss: 0.0837Epoch 33/50469/4694s8ms/step - loss: 0.0846 - val_loss: 0.0834Epoch 34/50469/4694s8ms/step - loss: 0.0846 - val_loss: 0.0832Epoch 35/50469/4694s8ms/step - loss: 0.0842 - val_loss: 0.0830Epoch 36/50469/4694s8ms/step - loss: 0.0841 - val_loss: 0.0829Epoch 37/50469/4694s8ms/step - loss: 0.0840 - val_loss: 0.0828Epoch 38/50469/4694s8ms/step - loss: 0.0839 - val_loss: 0.0825Epoch 39/50469/4694s8ms/step - loss: 0.0837 - val_loss: 0.0825Epoch 40/50469/4694s8ms/step - loss: 0.0836 - val_loss: 0.0823Epoch 41/50	469/469	4s	8ms/step	-	loss:	0.0849	-	<pre>val_loss:</pre>	0.0842
Epoch 33/50 469/469									
469/469 4s 8ms/step - loss: 0.0846 - val_loss: 0.0834 Epoch 34/50 469/469 4s 8ms/step - loss: 0.0846 - val_loss: 0.0832 Epoch 35/50 469/469 4s 8ms/step - loss: 0.0842 - val_loss: 0.0830 Epoch 36/50 4s 8ms/step - loss: 0.0841 - val_loss: 0.0829 Epoch 37/50 4s 8ms/step - loss: 0.0840 - val_loss: 0.0828 Epoch 38/50 4s 8ms/step - loss: 0.0839 - val_loss: 0.0825 Epoch 39/50 4s 8ms/step - loss: 0.0837 - val_loss: 0.0825 Epoch 40/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 41/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823	469/469	4s	8ms/step	-	loss:	0.0849	-	<pre>val_loss:</pre>	0.0837
## As &ms/step - loss: 0.0846 - val_loss: 0.0832 ## Epoch 35/50 ## 45 &ms/step - loss: 0.0842 - val_loss: 0.0830 ## Epoch 36/50 ## 45 &ms/step - loss: 0.0841 - val_loss: 0.0829 ## Epoch 37/50 ## 45 &ms/step - loss: 0.0841 - val_loss: 0.0829 ## Epoch 37/50 ## 45 &ms/step - loss: 0.0840 - val_loss: 0.0828 ## Epoch 38/50 ## 45 &ms/step - loss: 0.0839 - val_loss: 0.0825 ## Epoch 39/50 ## 45 &ms/step - loss: 0.0837 - val_loss: 0.0825 ## Epoch 40/50 ## 45 &ms/step - loss: 0.0836 - val_loss: 0.0823 ## Epoch 41/50									
469/469 4s 8ms/step - loss: 0.0846 - val_loss: 0.0832 Epoch 35/50 469/469 4s 8ms/step - loss: 0.0842 - val_loss: 0.0830 Epoch 36/50 4s 8ms/step - loss: 0.0841 - val_loss: 0.0829 Epoch 37/50 4s 8ms/step - loss: 0.0840 - val_loss: 0.0828 Epoch 38/50 4s 8ms/step - loss: 0.0839 - val_loss: 0.0825 Epoch 39/50 4s 8ms/step - loss: 0.0837 - val_loss: 0.0825 Epoch 40/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 41/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823	469/469	4s	8ms/step	-	loss:	0.0846	-	<pre>val_loss:</pre>	0.0834
Epoch 35/50 469/469	Epoch 34/50								
469/469 4s 8ms/step - loss: 0.0842 - val_loss: 0.0830 Epoch 36/50 4s 8ms/step - loss: 0.0841 - val_loss: 0.0829 Epoch 37/50 4s 8ms/step - loss: 0.0840 - val_loss: 0.0828 Epoch 38/50 4s 8ms/step - loss: 0.0839 - val_loss: 0.0825 Epoch 39/50 4s 8ms/step - loss: 0.0837 - val_loss: 0.0825 Epoch 40/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 40/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823	469/469	4s	8ms/step	-	loss:	0.0846	-	<pre>val_loss:</pre>	0.0832
Epoch 36/50 469/469	Epoch 35/50								
469/469 4s 8ms/step - loss: 0.0841 - val_loss: 0.0829 Epoch 37/50 469/469 4s 8ms/step - loss: 0.0840 - val_loss: 0.0828 Epoch 38/50 469/469 4s 8ms/step - loss: 0.0839 - val_loss: 0.0825 Epoch 39/50 4s 8ms/step - loss: 0.0837 - val_loss: 0.0825 Epoch 40/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 41/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823	469/469	4s	8ms/step	-	loss:	0.0842	-	<pre>val_loss:</pre>	0.0830
Epoch 37/50 469/469									
469/469 4s 8ms/step - loss: 0.0840 - val_loss: 0.0828 Epoch 38/50 469/469 4s 8ms/step - loss: 0.0839 - val_loss: 0.0825 Epoch 39/50 4s 8ms/step - loss: 0.0837 - val_loss: 0.0825 Epoch 40/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 41/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823	469/469	4s	8ms/step	-	loss:	0.0841	-	<pre>val_loss:</pre>	0.0829
Epoch 38/50 469/469	Epoch 37/50								
469/469 4s 8ms/step - loss: 0.0839 - val_loss: 0.0825 Epoch 39/50 469/469 4s 8ms/step - loss: 0.0837 - val_loss: 0.0825 Epoch 40/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 41/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823	469/469	4s	8ms/step	-	loss:	0.0840	-	<pre>val_loss:</pre>	0.0828
Epoch 39/50 469/469 — 4s 8ms/step - loss: 0.0837 - val_loss: 0.0825 Epoch 40/50 469/469 — 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 41/50	Epoch 38/50								
469/469 4s 8ms/step - loss: 0.0837 - val_loss: 0.0825 Epoch 40/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 41/50 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823	469/469	4 s	8ms/step	-	loss:	0.0839	-	<pre>val_loss:</pre>	0.0825
Epoch 40/50 469/469 — 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 41/50	Epoch 39/50								
469/469 4s 8ms/step - loss: 0.0836 - val_loss: 0.0823 Epoch 41/50	469/469	4s	8ms/step	-	loss:	0.0837	-	<pre>val_loss:</pre>	0.0825
Epoch 41/50	Epoch 40/50								
·	469/469	4s	8ms/step	-	loss:	0.0836	-	<pre>val_loss:</pre>	0.0823
469/469 4s 8ms/step - loss: 0.0835 - val_loss: 0.0822	Epoch 41/50								
	469/469 —————	4s	8ms/step	-	loss:	0.0835	-	<pre>val_loss:</pre>	0.0822

```
Epoch 42/50
469/469
                             4s 8ms/step - loss: 0.0834 - val loss: 0.0820
Epoch 43/50
                             4s 8ms/step - loss: 0.0829 - val loss: 0.0819
469/469 -
Epoch 44/50
                             4s 8ms/step - loss: 0.0831 - val loss: 0.0817
469/469 -
Epoch 45/50
                             4s 8ms/step - loss: 0.0827 - val loss: 0.0818
469/469
Epoch 46/50
                             4s 8ms/step - loss: 0.0828 - val loss: 0.0822
469/469 -
Epoch 47/50
                             4s 7ms/step - loss: 0.0825 - val loss: 0.0813
469/469 -
Epoch 48/50
                             4s 8ms/step - loss: 0.0826 - val loss: 0.0814
469/469 -
Epoch 49/50
                             4s 8ms/step - loss: 0.0823 - val loss: 0.0813
469/469
Epoch 50/50
                             4s 8ms/step - loss: 0.0824 - val loss: 0.0812
469/469
313/313 -
                             1s 3ms/step
```