

케라스, 텐서플로우 버전 확인

In [2]:

```
1 import keras
2 keras.__version__
```

Using TensorFlow backend.

Out[2]: '2.3.1'

In [3]:

```
1 import tensorflow as tf
2 tf.__version__
```

Out[3]: '2.0.0'

사용 라이브러리 및 이미지 불러오기

In [4]:

```
1 import warnings
2 warnings.filterwarnings('ignore')
3
4 from keras import models, layers
5 from keras.callbacks import ModelCheckpoint, EarlyStopping
6 import cv2
7 from glob import glob
8 import os
9 import numpy as np
10 from IPython.display import SVG
11 from keras.utils.vis_utils import model_to_dot
12 import tensorflow as tf
13 from tensorflow import keras
14
15 from keras import regularizers
16 from sklearn.model_selection import train_test_split
17 from tensorflow.keras.utils import to_categorical
18 from keras.models import Sequential
19 from keras.layers import Dense, Activation, Dropout, Flatten, Conv2D, MaxPooling2D, BatchNormalization
20 from keras.callbacks import ModelCheckpoint, EarlyStopping
21 import matplotlib.pyplot as plt
```

In [6]:

```
1 img_data = glob('C:\\\\Users\\WW82106\\Desktop\\sw_0601\\pokemon_g\\*.jpg')
2 class_name = ['Charmander', 'Gastly', 'Goldeen', 'Gyarados', 'Horsea', 'Mew', 'Mewtwo', 'Pikachu', 'Poliwag', 'Squirtle']
3 dic = {'Charmander':0, 'Gastly':1, 'Goldeen':2, 'Gyarados':3, 'Horsea':4, 'Mew':5, 'Mewtwo':6, 'Pikachu':7, 'Poliwag':8, 'Squirtle':9}
4 dic2 = {0:'Charmander', 1:'Gastly', 2:'Goldeen### 사용 라이브러리 및 이미지 불러오기', 3:'Gyarados', 4:'Horsea', 5:'Mew', 6:'Mewtwo'}
```

이미지, 레이블들을 저장

In [7]:

```
1 #데이터들을 담을 리스트 정의
2 X_all = list()
3 #레이블들을 담을 리스트 정의
4 Y_all = list()
5
6
7 for imagename in img_data:
8     try:
9         img = cv2.imread(imagename)
10        img = cv2.resize(img, dsize=(32, 32))
11        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
12
13        image = np.array(img)
14        X_all.append(img)
15
16        label = imagename.split('WW')
17        label = label[6]
18        label = label.split('.')
19        label = str(label[0])
20        label = dic[label]
21        Y_all.append(label)
22    except :
23        pass # 예외
24
25
26 # X, Y리스트들을 NP형식의 배열로 생성
27 X_all = np.array(X_all)
28 Y_all = np.array(Y_all)
29
30 print(X_all)
31 print(Y_all)
32 print('X_all shape: ', X_all.shape)
33 print('Y_all shape: ', Y_all.shape)
```

```
[[[ 0  0  0]
 [ 0  0  0]
 [ 0  0  0]
 ...
 [ 0  0  0]
 [ 0  0  0]
 [ 0  0  0]]

 [[ 0  0  0]
 [ 0  0  0]
 [ 0  0  0]
 ...
 [ 0  0  0]
 [ 0  0  0]
 [ 0  0  0]]

 [[ 0  0  0]
 [ 0  0  0]
 [ 0  0  0]
```

train, test 데이터셋 분리

In [8]:

```
1 X_train,X_test,Y_train,Y_test = train_test_split(X_all, Y_all, test_size = 0.2, shuffle=True, random_state=44)
2 print(X_train.shape)
3 print(X_test.shape)
4 print(Y_train.shape)
5 print(Y_test.shape)
```

```
(4169, 32, 32, 3)
(1043, 32, 32, 3)
(4169,)
(1043,)
```

정규화 및 원핫인코딩

```
In [9]: 1 X_train = X_train.reshape(X_train.shape[0], 32, 32, 3)
2 X_test = X_test.reshape(X_test.shape[0], 32, 32, 3)
3 X_train = X_train.astype('float') / 255
4 X_test = X_test.astype('float') / 255
5
6 print('X_train_shape: ', X_train.shape)
7 print('X_test_shape: ', X_test.shape)
8 print(X_train[:5])
9 print(X_test[:5])
```

X_train_shape: (4169, 32, 32, 3)
X_test_shape: (1043, 32, 32, 3)
[[[0. 0. 0.]
 [0. 0. 0.]
 [0. 0. 0.01960784]
 ...
 [0. 0. 0.]
 [0. 0. 0.]
 [0. 0. 0.]]

[[0. 0. 0.]
 [0. 0. 0.]
 [0.00392157 0. 0.05490196]
 ...
 [0. 0. 0.]
 [0. 0. 0.]
 [0. 0. 0.]]

[[0.16862745 0.16470588 0.29019608]
 [0.15004418 0.14001004 0.07050004]

```
In [10]: 1 Y_train = to_categorical(Y_train, 10)
2 Y_test = to_categorical(Y_test, 10)
3 print('Y_train_shape:', Y_train.shape)
4 print('Y_test_shape', Y_test.shape)
```

Y_train_shape: (4169, 10)
Y_test_shape (1043, 10)

CNN 인공지능 모델 설계

```
In [11]: 1 model = Sequential()
2 model.add(Conv2D(64, kernel_size=(5, 5), strides=(1, 1), padding='same',
3 activation='relu',
4 input_shape=(32, 32, 3)))
5 model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
6 model.add(Conv2D(32, (2, 2), activation='relu', padding='same'))
7 model.add(MaxPooling2D(pool_size=(2, 2)))
8 model.add(Dropout(0.25))
9 model.add(Flatten())
10 model.add(Dense(1000, activation='relu'))
11 model.add(Dropout(0.5))
12 model.add(Dense(10, activation='softmax'))
13 model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
=====		
conv2d_1 (Conv2D)	(None, 32, 32, 64)	4864

max_pooling2d_1 (MaxPooling2	(None, 16, 16, 64)	0

conv2d_2 (Conv2D)	(None, 16, 16, 32)	8224

max_pooling2d_2 (MaxPooling2	(None, 8, 8, 32)	0

dropout_1 (Dropout)	(None, 8, 8, 32)	0

flatten_1 (Flatten)	(None, 2048)	0

dense_1 (Dense)	(None, 1000)	2049000

dropout_2 (Dropout)	(None, 1000)	0

dense_2 (Dense)	(None, 10)	10010
=====		
Total params: 2,072,098		
Trainable params: 2,072,098		
Non-trainable params: 0		

모델 학습시키기

```
In [12]: 1 early_stopping = EarlyStopping(monitor = 'val_loss', patience=5, verbose=1)
2
3 model.compile(loss='categorical_crossentropy', optimizer='Adam', metrics=['accuracy'])
4 model.fit(X_train, Y_train, batch_size=40, epochs=40, verbose=1, callbacks = [early_stopping])
```

Epoch 1/40
4169/4169 [=====] - 8s 2ms/step - loss: 1.9583 - accuracy: 0.2934
Epoch 2/40
4169/4169 [=====] - 8s 2ms/step - loss: 1.3218 - accuracy: 0.5443
Epoch 3/40
4169/4169 [=====] - 8s 2ms/step - loss: 1.0322 - accuracy: 0.6397
Epoch 4/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.7959 - accuracy: 0.7373
Epoch 5/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.6260 - accuracy: 0.7961
Epoch 6/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.5070 - accuracy: 0.8340
Epoch 7/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.4290 - accuracy: 0.8568
Epoch 8/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.3308 - accuracy: 0.8897
Epoch 9/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.2853 - accuracy: 0.9103
Epoch 10/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.2362 - accuracy: 0.9240
Epoch 11/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.2287 - accuracy: 0.9252
Epoch 12/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.1883 - accuracy: 0.9381
Epoch 13/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.1723 - accuracy: 0.9472
Epoch 14/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.1279 - accuracy: 0.9590
Epoch 15/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.1433 - accuracy: 0.9532
Epoch 16/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0976 - accuracy: 0.9707
Epoch 17/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.1159 - accuracy: 0.9633
Epoch 18/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0933 - accuracy: 0.9751
Epoch 19/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0963 - accuracy: 0.9705
Epoch 20/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0968 - accuracy: 0.9715
Epoch 21/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0676 - accuracy: 0.9794
Epoch 22/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.1273 - accuracy: 0.9585
Epoch 23/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0709 - accuracy: 0.9784
Epoch 24/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0691 - accuracy: 0.9794
Epoch 25/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.1143 - accuracy: 0.9643
Epoch 26/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0597 - accuracy: 0.9813
Epoch 27/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0611 - accuracy: 0.9832
Epoch 28/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0435 - accuracy: 0.9873
Epoch 29/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0637 - accuracy: 0.9794
Epoch 30/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0639 - accuracy: 0.9782
Epoch 31/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0274 - accuracy: 0.9930
Epoch 32/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0395 - accuracy: 0.9875
Epoch 33/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0448 - accuracy: 0.9854
Epoch 34/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0548 - accuracy: 0.9825
Epoch 35/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0479 - accuracy: 0.9868
Epoch 36/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0382 - accuracy: 0.9868
Epoch 37/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0751 - accuracy: 0.9736
Epoch 38/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0461 - accuracy: 0.9832
Epoch 39/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0574 - accuracy: 0.9822
Epoch 40/40
4169/4169 [=====] - 8s 2ms/step - loss: 0.0386 - accuracy: 0.9875

Out[12]: <keras.callbacks.callbacks.History at 0x215663647f0>

CNN 모델 평가

In [13]:

1 score = model.evaluate(X_test, Y_test)

2 print('Test score:', score[0])

3 print('Test accuracy:', score[1])

1043/1043 [=====] - 1s 605us/step
Test score: 0.35320062333519714
Test accuracy: 0.9290508031845093

VGG16 - Transfer Learning

In [14]:

1 from tensorflow.keras import Input, models, layers, optimizers, metrics

2 from tensorflow.keras.layers import Dense, Flatten

3 from tensorflow.keras.applications import VGG16

VGG 모델 설계

```
In [44]: 1 transfer_model = VGG16(weights='imagenet', include_top=False, input_shape=(32, 32, 3))
2 transfer_model.trainable = False
3 transfer_model.summary()
4
5 finetune_model = models.Sequential()
6 finetune_model.add(transfer_model)
7 finetune_model.add(Flatten())
8 finetune_model.add(Dense(64, activation='relu'))
9 finetune_model.add(Dense(10, activation='softmax'))
10 finetune_model.summary()
```

Model: "vgg16"		
Layer (type)	Output Shape	Param #
=====		
input_5 (InputLayer)	[(None, 32, 32, 3)]	0
block1_conv1 (Conv2D)	(None, 32, 32, 64)	1792
block1_conv2 (Conv2D)	(None, 32, 32, 64)	36928
block1_pool (MaxPooling2D)	(None, 16, 16, 64)	0
block2_conv1 (Conv2D)	(None, 16, 16, 128)	73856
block2_conv2 (Conv2D)	(None, 16, 16, 128)	147584
block2_pool (MaxPooling2D)	(None, 8, 8, 128)	0
block3_conv1 (Conv2D)	(None, 8, 8, 256)	295168
block3_conv2 (Conv2D)	(None, 8, 8, 256)	590080
block3_conv3 (Conv2D)	(None, 8, 8, 256)	590080
block3_pool (MaxPooling2D)	(None, 4, 4, 256)	0
block4_conv1 (Conv2D)	(None, 4, 4, 512)	1180160
block4_conv2 (Conv2D)	(None, 4, 4, 512)	2359808
block4_conv3 (Conv2D)	(None, 4, 4, 512)	2359808
block4_pool (MaxPooling2D)	(None, 2, 2, 512)	0
block5_conv1 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv2 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv3 (Conv2D)	(None, 2, 2, 512)	2359808
block5_pool (MaxPooling2D)	(None, 1, 1, 512)	0
=====		
Total params: 14,714,688		
Trainable params: 0		
Non-trainable params: 14,714,688		
Model: "sequential_7"		
Layer (type)	Output Shape	Param #
=====		
vgg16 (Model)	(None, 1, 1, 512)	14714688
flatten_4 (Flatten)	(None, 512)	0
dense_8 (Dense)	(None, 64)	32832
dense_9 (Dense)	(None, 10)	650
=====		
Total params: 14,748,170		
Trainable params: 33,482		
Non-trainable params: 14,714,688		

모델 학습시키기

In [45]:

```
1 finetune_model.compile(loss='categorical_crossentropy', optimizer=optimizers.Adam(learning_rate=0.0002), metrics=['accuracy']
2 t_history = finetune_model.fit(X_train, Y_train, batch_size=50, epochs=30, validation_data=(X_test, Y_test))
```

Train on 4169 samples, validate on 1043 samples

Epoch 1/30
4169/4169 [=====] - 18s 4ms/sample - loss: 2.1986 - accuracy: 0.2231 - val_loss: 2.0290 - val_accuracy: 0.3384

Epoch 2/30
4169/4169 [=====] - 17s 4ms/sample - loss: 1.8648 - accuracy: 0.4118 - val_loss: 1.7925 - val_accuracy: 0.4343

Epoch 3/30
4169/4169 [=====] - 17s 4ms/sample - loss: 1.6457 - accuracy: 0.4872 - val_loss: 1.6056 - val_accuracy: 0.4995

Epoch 4/30
4169/4169 [=====] - 17s 4ms/sample - loss: 1.4880 - accuracy: 0.5395 - val_loss: 1.4860 - val_accuracy: 0.5312

Epoch 5/30
4169/4169 [=====] - 17s 4ms/sample - loss: 1.3756 - accuracy: 0.5682 - val_loss: 1.3960 - val_accuracy: 0.5618

Epoch 6/30
4169/4169 [=====] - 17s 4ms/sample - loss: 1.2830 - accuracy: 0.6011 - val_loss: 1.3279 - val_accuracy: 0.5733

Epoch 7/30
4169/4169 [=====] - 17s 4ms/sample - loss: 1.2057 - accuracy: 0.6222 - val_loss: 1.2510 - val_accuracy: 0.6012

Epoch 8/30
4169/4169 [=====] - 17s 4ms/sample - loss: 1.1378 - accuracy: 0.6472 - val_loss: 1.1999 - val_accuracy: 0.6203

Epoch 9/30
4169/4169 [=====] - 17s 4ms/sample - loss: 1.0818 - accuracy: 0.6647 - val_loss: 1.1515 - val_accuracy: 0.6337

Epoch 10/30
4169/4169 [=====] - 17s 4ms/sample - loss: 1.0303 - accuracy: 0.6803 - val_loss: 1.1131 - val_accuracy: 0.6453 - accu

Epoch 11/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.9864 - accuracy: 0.6947 - val_loss: 1.0736 - val_accuracy: 0.6673

Epoch 12/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.9435 - accuracy: 0.7141 - val_loss: 1.0369 - val_accuracy: 0.6683

Epoch 13/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.9077 - accuracy: 0.7227 - val_loss: 1.0103 - val_accuracy: 0.6807

Epoch 14/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.8716 - accuracy: 0.7366 - val_loss: 0.9758 - val_accuracy: 0.6855

Epoch 15/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.8395 - accuracy: 0.7477 - val_loss: 0.9539 - val_accuracy: 0.7057

Epoch 16/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.8098 - accuracy: 0.7587 - val_loss: 0.9344 - val_accuracy: 0.7114

Epoch 17/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.7815 - accuracy: 0.7690 - val_loss: 0.9114 - val_accuracy: 0.7124

Epoch 18/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.7559 - accuracy: 0.7757 - val_loss: 0.8889 - val_accuracy: 0.7315

Epoch 19/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.7294 - accuracy: 0.7868 - val_loss: 0.8685 - val_accuracy: 0.7258

Epoch 20/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.7069 - accuracy: 0.7992 - val_loss: 0.8432 - val_accuracy: 0.7450

Epoch 21/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.6846 - accuracy: 0.8071 - val_loss: 0.8302 - val_accuracy: 0.7411

Epoch 22/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.6621 - accuracy: 0.8119 - val_loss: 0.8209 - val_accuracy: 0.7450

Epoch 23/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.6425 - accuracy: 0.8179 - val_loss: 0.7934 - val_accuracy: 0.7661

Epoch 24/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.6242 - accuracy: 0.8261 - val_loss: 0.7932 - val_accuracy: 0.7613

Epoch 25/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.6050 - accuracy: 0.8319 - val_loss: 0.7636 - val_accuracy: 0.7593

Epoch 26/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.5881 - accuracy: 0.8398 - val_loss: 0.7567 - val_accuracy: 0.7709

Epoch 27/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.5712 - accuracy: 0.8462 - val_loss: 0.7499 - val_accuracy: 0.7670

Epoch 28/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.5562 - accuracy: 0.8460 - val_loss: 0.7321 - val_accuracy: 0.7785

Epoch 29/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.5381 - accuracy: 0.8554 - val_loss: 0.7243 - val_accuracy: 0.7795
Epoch 30/30
4169/4169 [=====] - 17s 4ms/sample - loss: 0.5239 - accuracy: 0.8626 - val_loss: 0.7109 - val_accuracy: 0.7919

VGG16 모델 평가

In [47]:

1 score = finetune_model.evaluate(X_test, Y_test)

2 print('Test score:', score[0])

3 print('Test accuracy:', score[1])

1043/1 [=====

Autoencoder - Unsupervised Learning


```
In [55]: 1 autoencoder = Sequential()
2
3 # 인코딩 부분입니다.
4 autoencoder.add(Conv2D(16, kernel_size=3, padding='same', input_shape=(32,32,3), activation='relu'))
5 autoencoder.add(MaxPooling2D(pool_size=2, padding='same'))
6 autoencoder.add(Conv2D(8, kernel_size=3, activation='relu', padding='same'))
7 autoencoder.add(MaxPooling2D(pool_size=2, padding='same'))
8 autoencoder.add(Conv2D(8, kernel_size=3, strides=2, padding='same', activation='relu'))
9
10 # 디코딩 부분이 이어집니다.
11 autoencoder.add(Conv2D(8, kernel_size=3, padding='same', activation='relu'))
12 autoencoder.add(UpSampling2D())
13 autoencoder.add(Conv2D(8, kernel_size=3, padding='same', activation='relu'))
14 autoencoder.add(UpSampling2D())
15 #autoencoder.add(Conv2D(16, kernel_size=3, activation='relu'))
16 autoencoder.add(UpSampling2D())
17 autoencoder.add(Conv2D(3, kernel_size=3, padding='same', activation='sigmoid'))
18
19 # 전체 구조를 확인해 봅니다.
20 autoencoder.summary()
21
22 # 컴파일 및 학습을 하는 부분입니다.
23 autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
24 autoencoder.fit(X_train, X_train, epochs=50, batch_size=100, validation_data=(X_test, X_test))
```

Model: "sequential_12"

Layer (type)	Output Shape	Param #
=====		
conv2d_53 (Conv2D)	(None, 32, 32, 16)	448

max_pooling2d_16 (MaxPooling)	(None, 16, 16, 16)	0

conv2d_54 (Conv2D)	(None, 16, 16, 8)	1160

max_pooling2d_17 (MaxPooling)	(None, 8, 8, 8)	0

conv2d_55 (Conv2D)	(None, 4, 4, 8)	584

conv2d_56 (Conv2D)	(None, 4, 4, 8)	584

up_sampling2d_23 (UpSampling)	(None, 8, 8, 8)	0

conv2d_57 (Conv2D)	(None, 8, 8, 8)	584

up_sampling2d_24 (UpSampling)	(None, 16, 16, 8)	0

up_sampling2d_25 (UpSampling)	(None, 32, 32, 8)	0

conv2d_58 (Conv2D)	(None, 32, 32, 3)	219
=====		

Total params: 3,579
Trainable params: 3,579
Non-trainable params: 0

Train on 4169 samples, validate on 1043 samples
Epoch 1/50
4169/4169 [=====] - 4s 952us/sample - loss: 0.6478 - val_loss: 0.5968
Epoch 2/50
4169/4169 [=====] - 3s 816us/sample - loss: 0.5724 - val_loss: 0.5530
Epoch 3/50
4169/4169 [=====] - 3s 826us/sample - loss: 0.5383 - val_loss: 0.5132
Epoch 4/50
4169/4169 [=====] - 3s 829us/sample - loss: 0.5080 - val_loss: 0.4942
Epoch 5/50
4169/4169 [=====] - 4s 840us/sample - loss: 0.4950 - val_loss: 0.4864
Epoch 6/50
4169/4169 [=====] - 3s 833us/sample - loss: 0.4868 - val_loss: 0.4787
Epoch 7/50
4169/4169 [=====] - 3s 832us/sample - loss: 0.4804 - val_loss: 0.4714
Epoch 8/50
4169/4169 [=====] - 3s 825us/sample - loss: 0.4721 - val_loss: 0.4629
Epoch 9/50
4169/4169 [=====] - 3s 834us/sample - loss: 0.4655 - val_loss: 0.4592
Epoch 10/50
4169/4169 [=====] - 4s 844us/sample - loss: 0.4621 - val_loss: 0.4561
Epoch 11/50
4169/4169 [=====] - 3s 827us/sample - loss: 0.4593 - val_loss: 0.4536
Epoch 12/50
4169/4169 [=====] - 4s 842us/sample - loss: 0.4573 - val_loss: 0.4519
Epoch 13/50
4169/4169 [=====] - 3s 834us/sample - loss: 0.4551 - val_loss: 0.4503
Epoch 14/50
4169/4169 [=====] - 3s 838us/sample - loss: 0.4536 - val_loss: 0.4485
Epoch 15/50
4169/4169 [=====] - 3s 837us/sample - loss: 0.4520 - val_loss: 0.4474
Epoch 16/50
4169/4169 [=====] - 3s 838us/sample - loss: 0.4505 - val_loss: 0.4460

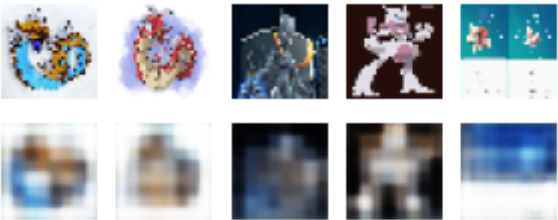
Epoch 17/50
4169/4169 [=====] - 4s 935us/sample - loss: 0.4494 - val_loss: 0.4450
Epoch 18/50
4169/4169 [=====] - 4s 858us/sample - loss: 0.4480 - val_loss: 0.4436
Epoch 19/50
4169/4169 [=====] - 4s 858us/sample - loss: 0.4468 - val_loss: 0.4424
Epoch 20/50
4169/4169 [=====] - 4s 852us/sample - loss: 0.4455 - val_loss: 0.4414
Epoch 21/50
4169/4169 [=====] - 4s 852us/sample - loss: 0.4447 - val_loss: 0.4408
Epoch 22/50
4169/4169 [=====] - 4s 847us/sample - loss: 0.4439 - val_loss: 0.4399
Epoch 23/50
4169/4169 [=====] - 4s 859us/sample - loss: 0.4426 - val_loss: 0.4390
Epoch 24/50
4169/4169 [=====] - 4s 843us/sample - loss: 0.4417 - val_loss: 0.4381
Epoch 25/50
4169/4169 [=====] - 3s 838us/sample - loss: 0.4406 - val_loss: 0.4366
Epoch 26/50
4169/4169 [=====] - 3s 828us/sample - loss: 0.4398 - val_loss: 0.4357
Epoch 27/50
4169/4169 [=====] - 3s 837us/sample - loss: 0.4390 - val_loss: 0.4353
Epoch 28/50
4169/4169 [=====] - 3s 833us/sample - loss: 0.4383 - val_loss: 0.4343
Epoch 29/50
4169/4169 [=====] - 4s 842us/sample - loss: 0.4379 - val_loss: 0.4336
Epoch 30/50
4169/4169 [=====] - 3s 837us/sample - loss: 0.4368 - val_loss: 0.4334
Epoch 31/50
4169/4169 [=====] - 3s 827us/sample - loss: 0.4364 - val_loss: 0.4324
Epoch 32/50
4169/4169 [=====] - 4s 844us/sample - loss: 0.4358 - val_loss: 0.4326
Epoch 33/50
4169/4169 [=====] - 3s 834us/sample - loss: 0.4353 - val_loss: 0.4314
Epoch 34/50
4169/4169 [=====] - 3s 835us/sample - loss: 0.4350 - val_loss: 0.4312
Epoch 35/50
4169/4169 [=====] - 3s 831us/sample - loss: 0.4344 - val_loss: 0.4316
Epoch 36/50
4169/4169 [=====] - 3s 826us/sample - loss: 0.4341 - val_loss: 0.4301
Epoch 37/50
4169/4169 [=====] - 4s 851us/sample - loss: 0.4335 - val_loss: 0.4300
Epoch 38/50
4169/4169 [=====] - 3s 837us/sample - loss: 0.4331 - val_loss: 0.4294
Epoch 39/50
4169/4169 [=====] - 4s 848us/sample - loss: 0.4329 - val_loss: 0.4294
Epoch 40/50
4169/4169 [=====] - 3s 826us/sample - loss: 0.4327 - val_loss: 0.4294
Epoch 41/50
4169/4169 [=====] - 3s 823us/sample - loss: 0.4323 - val_loss: 0.4285
Epoch 42/50
4169/4169 [=====] - 3s 825us/sample - loss: 0.4321 - val_loss: 0.4283
Epoch 43/50
4169/4169 [=====] - 3s 822us/sample - loss: 0.4316 - val_loss: 0.4280
Epoch 44/50
4169/4169 [=====] - 3s 823us/sample - loss: 0.4319 - val_loss: 0.4280
Epoch 45/50
4169/4169 [=====] - 3s 820us/sample - loss: 0.4312 - val_loss: 0.4275
Epoch 46/50
4169/4169 [=====] - 3s 834us/sample - loss: 0.4311 - val_loss: 0.4279
Epoch 47/50
4169/4169 [=====] - 3s 830us/sample - loss: 0.4306 - val_loss: 0.4270
Epoch 48/50
4169/4169 [=====] - 3s 834us/sample - loss: 0.4305 - val_loss: 0.4266
Epoch 49/50
4169/4169 [=====] - 3s 837us/sample - loss: 0.4303 - val_loss: 0.4272
Epoch 50/50
4169/4169 [=====] - 4s 841us/sample - loss: 0.4300 - val_loss: 0.4263

Out[55]: <tensorflow.python.keras.callbacks.History at 0x2150d052710>

결과 출력

In [56]:

```
1 #학습된 결과를 출력하는 부분입니다.
2 random_test = np.random.randint(X_test.shape[0], size=5) #테스트할 이미지를 랜덤하게 불러옵니다.
3 ae_imgs = autoencoder.predict(X_test) #앞서 만든 오토인코더 모델에 집어 넣습니다.
4
5 plt.figure(figsize=(7, 2)) #출력될 이미지의 크기
6
7 for i, image_idx in enumerate(random_test): #랜덤하게 뽑은 이미지를 차례로 나열
8     ax = plt.subplot(2, 7, i + 1) ### VGG16 - Transfer Learning
9     plt.imshow(X_test[image_idx].reshape(32, 32, 3)) #테스트할 이미지
10    ax.axis('off')
11    ax = plt.subplot(2, 7, 7 + i + 1)
12    plt.imshow(ae_imgs[image_idx].reshape(32, 32, 3)) #오토인코딩 결과를 다음열에 출력
13    ax.axis('off')
14
15 plt.show()
```



In [54]:

```
1 #학습된 결과를 출력하는 부분입니다.
2 random_test = np.random.randint(X_test.shape[0], size=5) #테스트할 이미지를 랜덤하게 불러옵니다.
3 ae_imgs = autoencoder.predict(X_test) #앞서 만든 오토인코더 모델에 집어 넣습니다.
4
5 plt.figure(figsize=(7, 2)) #출력될 이미지의 크기
6
7 for i, image_idx in enumerate(random_test): #랜덤하게 뽑은 이미지를 차례로 나열
8     ax = plt.subplot(2, 7, i + 1)
9     plt.imshow(X_test[image_idx].reshape(32, 32, 3)) #테스트할 이미지
10    ax.axis('off')
11    ax = plt.subplot(2, 7, 7 + i + 1)
12    plt.imshow(ae_imgs[image_idx].reshape(32, 32, 3)) #오토인코딩 결과를 다음열에 출력
13    ax.axis('off')
14
15 plt.show()
```

