# 종합실습2_MNIST

## 1.환경준비

### (1) 라이브러리 로딩

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.metrics import *
from sklearn.preprocessing import StandardScaler, MinMaxScaler

from keras.models import Sequential
from keras.layers import Dense, Flatten
from keras.backend import clear_session
from keras.optimizers import Adam
from keras.datasets import mnist, fashion_mnist
```

- 함수 만들기

```
# 학습곡선 함수
def dl_history_plot(history):
    plt.figure(figsize=(10,6))
    plt.plot(history['loss'], label='train_err')
    plt.plot(history['val_loss'], label='val_err')

    plt.ylabel('Loss')
    plt.xlabel('Epoch')
    plt.legend()
    plt.grid()
    plt.show()
```

### (2) 데이터로딩

```
# 케라스 데이터셋으로 부터 mnist 불러오기
(x_train, y_train), (x_val, y_val) = mnist.load_data() # 튜플 형태로 반환
```

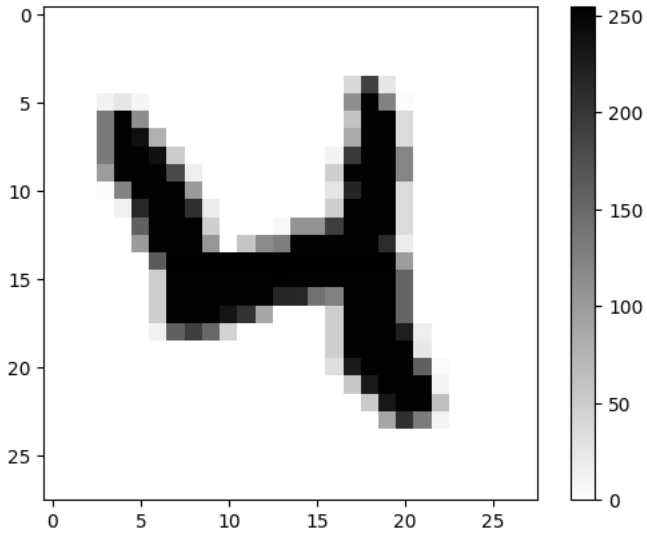
```
x_train.shape, y_train.shape
```

```
((60000, 28, 28), (60000,))
```

```
class_names = ['0','1','2','3','4','5','6','7','8','9']
```

## 2 데이터 살펴보기

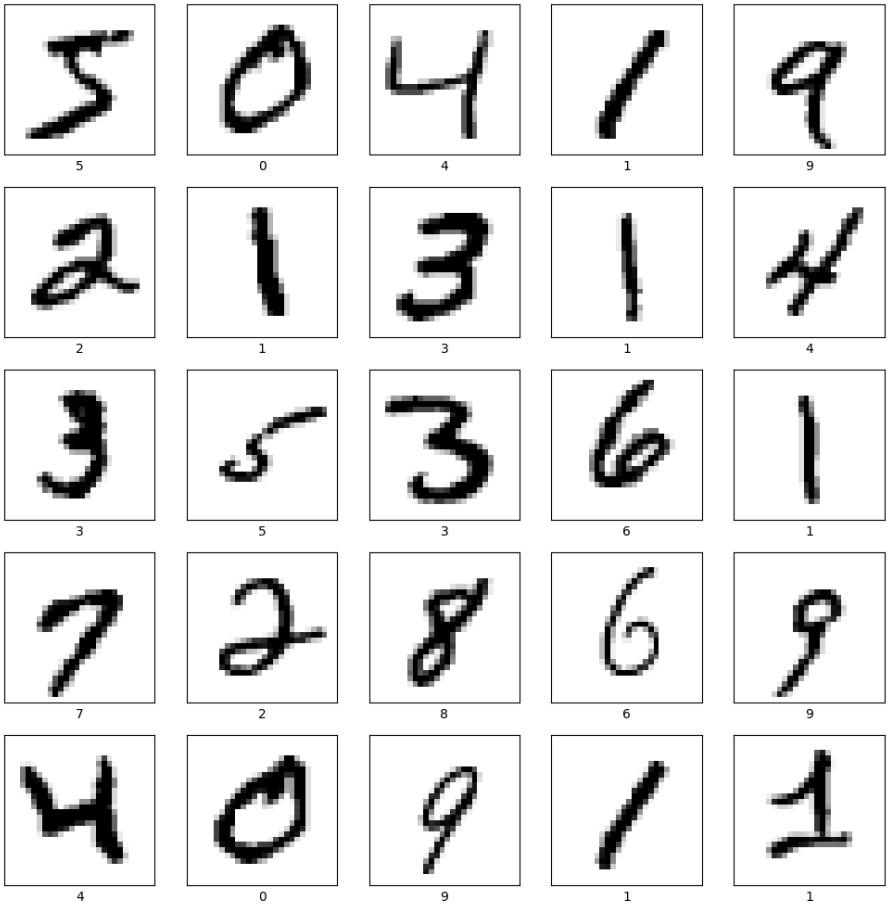
```
# 아래 숫자를 바꿔가며 화면에 그려 봅시다.
n = 20

plt.figure()
plt.imshow(x_train[n], cmap=plt.cm.binary)
plt.colorbar()
plt.show()
```




```
# 옵션추가해주세요.
np.set_printoptions(linewidth= np.inf)
x_train[n]
```

ndarray (28, 28) show data

```
plt.figure(figsize=(10,10))
for i in range(25):
    plt.subplot(5,5,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.imshow(x_train[i], cmap=plt.cm.binary)
    plt.xlabel(class_names[y_train[i]])
plt.tight_layout()
plt.show()
```




## 3.데이터 준비

### (1) 데이터 2차원으로 펼치기

```
x_train.shape, y_train.shape, x_val.shape, y_val.shape
```

```
((60000, 28, 28), (60000,), (10000, 28, 28), (10000,))
```

```
a = np.array([[1,2,3],[4,5,6]])
a, a.shape
```

```
(array([[1, 2, 3],
        [4, 5, 6]]),
 (2, 3))
```

```
#
print(a.reshape(3,2))
print(a.reshape(6,1))
print(a.reshape(6, -1))
```

```
[[1 2]
 [3 4]
 [5 6]]
[[1]
 [2]
 [3]
 [4]
 [5]
 [6]]
[[1]
 [2]
 [3]
 [4]
 [5]
 [6]]
```

```
x_train = x_train.reshape(60000, -1)
x_val = x_val.reshape(10000, -1)
```

```
x_train.shape, x_val.shape
```

```
((60000, 784), (10000, 784))
```

### (2) Scaling : Min-Max

- 0-255 값으로 되어 있는 데이터를 0-1사이 값으로 변환
- x_train, x_val를 그냥 255로 나누면 됨

```
x_train = x_train / 255
x_val = x_val / 255
```

## 4.모델링

```
nfeatures = x_train.shape[1]
nfeatures
```

```
784
```

```
clear_session()

model = Sequential(Dense(10, input_shape = (nfeatures,), activation = 'softmax'))

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 10)                7850

=================================================================
Total params: 7850 (30.66 KB)
Trainable params: 7850 (30.66 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

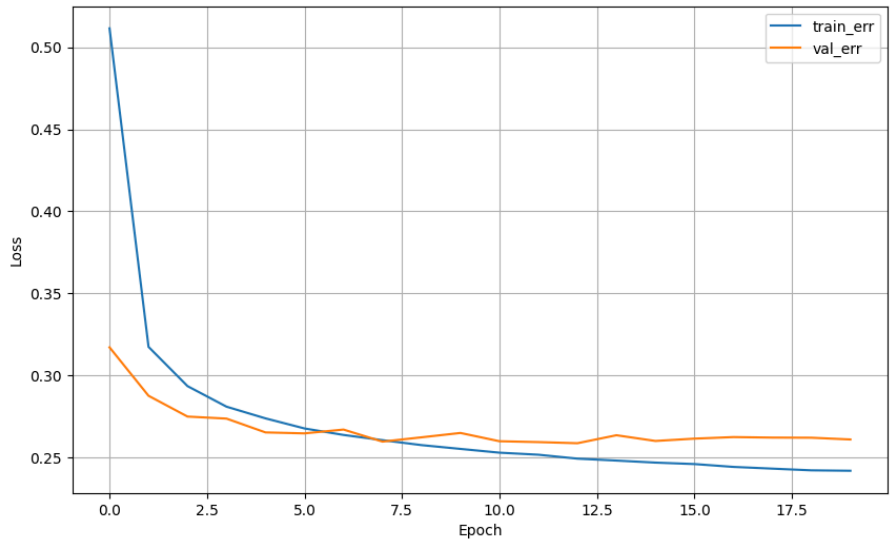
```
model.compile(optimizer=Adam(learning_rate=0.001), loss= 'sparse_categorical_crossentropy' )

history = model.fit(x_train, y_train, epochs = 20, validation_split=0.2).history
```

```
Epoch 1/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.5116 - val_loss: 0.3171
Epoch 2/20
1500/1500 [==============================] - 4s 3ms/step - loss: 0.3174 - val_loss: 0.2876
Epoch 3/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2935 - val_loss: 0.2749
Epoch 4/20
```

```
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2809 - val_loss: 0.2737
Epoch 5/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2738 - val_loss: 0.2652
Epoch 6/20
1500/1500 [==============================] - 4s 3ms/step - loss: 0.2677 - val_loss: 0.2647
Epoch 7/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2637 - val_loss: 0.2670
Epoch 8/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2605 - val_loss: 0.2596
Epoch 9/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2575 - val_loss: 0.2623
Epoch 10/20
1500/1500 [==============================] - 4s 3ms/step - loss: 0.2552 - val_loss: 0.2649
Epoch 11/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2529 - val_loss: 0.2599
Epoch 12/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2517 - val_loss: 0.2593
Epoch 13/20
1500/1500 [==============================] - 4s 3ms/step - loss: 0.2493 - val_loss: 0.2587
Epoch 14/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2481 - val_loss: 0.2635
Epoch 15/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2468 - val_loss: 0.2600
Epoch 16/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2460 - val_loss: 0.2615
Epoch 17/20
1500/1500 [==============================] - 4s 3ms/step - loss: 0.2442 - val_loss: 0.2624
Epoch 18/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2432 - val_loss: 0.2621
Epoch 19/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2421 - val_loss: 0.2620
Epoch 20/20
1500/1500 [==============================] - 3s 2ms/step - loss: 0.2419 - val_loss: 0.2609
```

- 학습결과 그래프

```
dl_history_plot(history)
```




- 예측 및 평가

```
pred = model.predict(x_val)
pred_1 = pred.argmax(axis=1)
```

```
313/313 [==============================] - 1s 1ms/step
```

```
print(confusion_matrix(y_val, pred_1))
print(classification_report(y_val, pred_1))
```

```
[[ 965    0    0    2    1    5    4    2    1    0]
 [   0 1110    3    2    0    1    3    2   14    0]
 [   7   10  919   16    8    4   12   11   42    3]
 [   4    0   15  919    2   24    2   11   26    7]
 [   1    1    7    2  928    0    6    6   10   21]
 [   9    2    5   29    9  787   11    9   27    4]
 [  14    3    9    1    8   16  904    1    2    0]
 [   2    7   18    7    7    0    0  959    3   25]
 [  10    6    6   20    9   22    5   12  877    7]
 [  11    7    1   10   34    5    0   35    8  898]]
              precision    recall  f1-score   support

           0       0.94      0.98      0.96       980
           1       0.97      0.98      0.97      1135
           2       0.93      0.89      0.91      1032
           3       0.91      0.91      0.91      1010
           4       0.92      0.95      0.93       982
           5       0.91      0.88      0.90       892
           6       0.95      0.94      0.95       958
           7       0.92      0.93      0.92      1028
           8       0.87      0.90      0.88       974
           9       0.93      0.89      0.91      1009

    accuracy                           0.93     10000
   macro avg       0.93      0.93      0.93     10000
weighted avg       0.93      0.93      0.93     10000
```

## 5.실습

- 히든레이어를 추가하여 모델을 2가지 이상 만들고 성능을 비교해 봅시다.
- 성능에 영향을 주는 요인은
  - 히든레이어 수
  - 노드수
  - epochs 수 (10~20 사이에서 정하세요)
  - learning_rate

### (1) 모델1

```
n = x_train.shape[1]
n
```

```
784
```

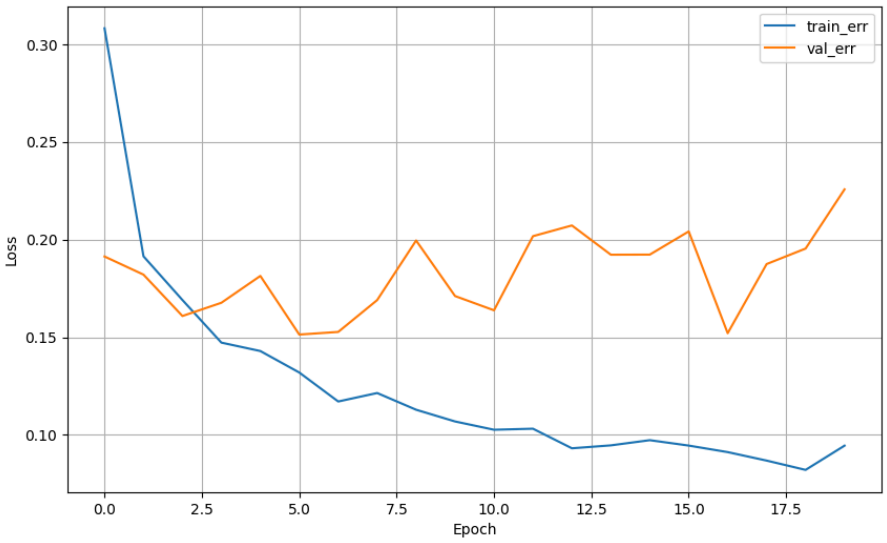
```
clear_session()
model = Sequential([Dense(64, input_shape=(n, ), activation='relu'),
                    Dense(32, activation='relu'),
                   Dense(16, activation='relu'),
                    Dense(10, activation='softmax')])
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 64)                50240

 dense_1 (Dense)             (None, 32)                2080

 dense_2 (Dense)             (None, 16)                528

 dense_3 (Dense)             (None, 10)                170

=================================================================
Total params: 53018 (207.10 KB)
Trainable params: 53018 (207.10 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
model.compile(optimizer=Adam(0.01), loss='sparse_categorical_crossentropy')
hist = model.fit(x_train, y_train, epochs=20, validation_split=.2).history
```

```
Epoch 1/20
1500/1500 [==============================] - 8s 5ms/step - loss: 0.3081 - val_loss: 0.1913
Epoch 2/20
1500/1500 [==============================] - 5s 3ms/step - loss: 0.1914 - val_loss: 0.1820
Epoch 3/20
1500/1500 [==============================] - 6s 4ms/step - loss: 0.1690 - val_loss: 0.1608
Epoch 4/20
1500/1500 [==============================] - 5s 3ms/step - loss: 0.1472 - val_loss: 0.1676
Epoch 5/20
1500/1500 [==============================] - 6s 4ms/step - loss: 0.1429 - val_loss: 0.1813
Epoch 6/20
1500/1500 [==============================] - 5s 3ms/step - loss: 0.1319 - val_loss: 0.1513
Epoch 7/20
1500/1500 [==============================] - 5s 3ms/step - loss: 0.1171 - val_loss: 0.1527
Epoch 8/20
1500/1500 [==============================] - 6s 4ms/step - loss: 0.1214 - val_loss: 0.1690
Epoch 9/20
1500/1500 [==============================] - 5s 3ms/step - loss: 0.1129 - val_loss: 0.1995
Epoch 10/20
1500/1500 [==============================] - 6s 4ms/step - loss: 0.1069 - val_loss: 0.1711
Epoch 11/20
1500/1500 [==============================] - 5s 3ms/step - loss: 0.1026 - val_loss: 0.1638
Epoch 12/20
1500/1500 [==============================] - 6s 4ms/step - loss: 0.1032 - val_loss: 0.2017
Epoch 13/20
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0931 - val_loss: 0.2072
Epoch 14/20
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0946 - val_loss: 0.1922
Epoch 15/20
1500/1500 [==============================] - 6s 4ms/step - loss: 0.0973 - val_loss: 0.1923
Epoch 16/20
1500/1500 [==============================] - 5s 3ms/step - loss: 0.0945 - val_loss: 0.2041
Epoch 17/20
1500/1500 [==============================] - 7s 5ms/step - loss: 0.0912 - val_loss: 0.1520
Epoch 18/20
1500/1500 [==============================] - 5s 4ms/step - loss: 0.0868 - val_loss: 0.1874
Epoch 19/20
1500/1500 [==============================] - 6s 4ms/step - loss: 0.0821 - val_loss: 0.1954
Epoch 20/20
1500/1500 [==============================] - 5s 4ms/step - loss: 0.0945 - val_loss: 0.2256
```

```
dl_history_plot(hist)
```




```
pred = model.predict(x_val)
pred = np.argmax(pred, axis=1)
```

```
313/313 [==============================] - 1s 2ms/step
```

```
print(confusion_matrix(y_val, pred_1))
print(classification_report(y_val, pred_1))
```

```
[[ 965    0    0    2    1    5    4    2    1    0]
 [   0 1110    3    2    0    1    3    2   14    0]
 [   7   10  919   16    8    4   12   11   42    3]
 [   4    0   15  919    2   24    2   11   26    7]
 [   1    1    7    2  928    0    6    6   10   21]
 [   9    2    5   29    9  787   11    9   27    4]
 [  14    3    9    1    8   16  904    1    2    0]
 [   2    7   18    7    7    0    0  959    3   25]
 [  10    6    6   20    9   22    5   12  877    7]
 [  11    7    1   10   34    5    0   35    8  898]]
              precision    recall  f1-score   support

           0       0.94      0.98      0.96       980
           1       0.97      0.98      0.97      1135
           2       0.93      0.89      0.91      1032
           3       0.91      0.91      0.91      1010
           4       0.92      0.95      0.93       982
           5       0.91      0.88      0.90       892
           6       0.95      0.94      0.95       958
           7       0.92      0.93      0.92      1028
           8       0.87      0.90      0.88       974
           9       0.93      0.89      0.91      1009

    accuracy                           0.93     10000
   macro avg       0.93      0.93      0.93     10000
weighted avg       0.93      0.93      0.93     10000
```

## (2) 모델2

```
n
```

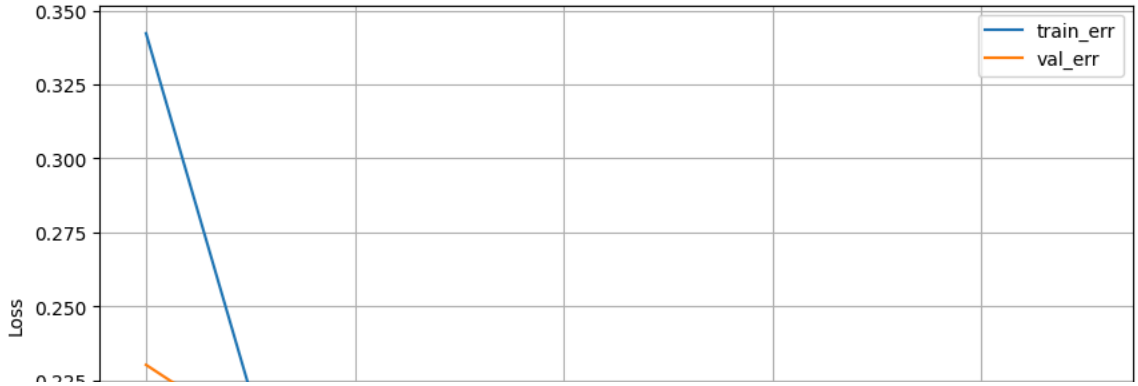
```
784
```

```
clear_session()
model = Sequential([Dense(32, input_shape=(n, ), activation='relu'),
                    Dense(16, activation='relu'),
                    Dense(10, activation='softmax')])
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 32)                25120

 dense_1 (Dense)             (None, 16)                528

 dense_2 (Dense)             (None, 10)                170

=================================================================
Total params: 25818 (100.85 KB)
Trainable params: 25818 (100.85 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
model.compile(optimizer=Adam(0.01), loss='sparse_categorical_crossentropy')
hist = model.fit(x_train, y_train, epochs=10, validation_split=.2, verbose = 0).history
```

```
dl_history_plot(hist)
```




```
pred = model.predict(x_val)
pred = np.argmax(pred, axis=1)
```

```
313/313 [==============================] - 1s 4ms/step
```

```
print(confusion_matrix(y_val, pred_1))
print(classification_report(y_val, pred_1))
```

```
[[ 965    0    0    2    1    5    4    2    1    0]
 [   0 1110    3    2    0    1    3    2   14    0]
 [   7   10  919   16    8    4   12   11   42    3]
 [   4    0   15  919    2   24    2   11   26    7]
 [   1    1    7    2  928    0    6    6   10   21]
 [   9    2    5   29    9  787   11    9   27    4]
 [  14    3    9    1    8   16  904    1    2    0]
 [   2    7   18    7    7    0    0  959    3   25]
 [  10    6    6   20    9   22    5   12  877    7]
 [  11    7    1   10   34    5    0   35    8  898]]
              precision    recall  f1-score   support

           0       0.94      0.98      0.96       980
           1       0.97      0.98      0.97      1135
           2       0.93      0.89      0.91      1032
           3       0.91      0.91      0.91      1010
           4       0.92      0.95      0.93       982
           5       0.91      0.88      0.90       892
```