딥러닝3 : 다중분류

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 MinMaxScaler

from keras.models import Sequential
from keras.layers import Dense
from keras.backend import clear_session
from keras.optimizers import Adam
```

- 함수 만들기

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

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

(2) 데이터로딩

```
path = "https://raw.githubusercontent.com/DA4BAM/dataset/master/iris.csv"
data = pd.read_csv(path)
data.head()
```

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

Next steps: Generate code with data View recommended plots

2.데이터 준비

```
# np.argmax()
a = np.array([[1,2,3],[3,1,2]])
a
```

```
array([[1, 2, 3],
       [3, 1, 2]])
```

```
np.argmax(a, axis = 0)
```

```
array([1, 0, 0])
```

```
np.argmax(a, axis = 1)
```

```
array([2, 0])
```

```
np.argmax(a)
```

```
2
```

(1) y 값을 0,1,2로 변환하기

(sparse_categorical_crossentropy 사용을 위해)

```
data['Species'] = data['Species'].map({'setosa':0, 'versicolor':1, 'virginica':2})
data.head()
```

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0

Next steps: Generate code with data View recommended plots

(2) 데이터 준비

```
target = 'Species'
x = data.drop(target, axis = 1)
y = data.loc[:, target]
```

(3) 데이터 분할 : train : val

```
x.head()
```

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

Next steps: Generate code with x View recommended plots

```
y.head()
```

```
0    0
1    0
2    0
3    0
4    0
Name: Species, dtype: int64
```

```
x_train, x_val, y_train, y_val = train_test_split(x, y, test_size = .3, random_state = 20)
```

(4) Scaling

```
scaler = MinMaxScaler()
x_train = scaler.fit_transform(x_train)
x_val = scaler.transform(x_val)
```

3.모델링1

(1) 모델 설계

```
nfeatures = x_train.shape[1] #num of columns
nfeatures
```

```
4
```

```
# 메모리 정리
clear_session()

# Sequential # 예측한 값을, 하나의 확률 값으로 변환
model = Sequential( Dense( 3 , input_shape = (nfeatures,), activation = 'softmax') )

# 모델요약
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 3)                 15

=================================================================
Total params: 15 (60.00 Byte)
Trainable params: 15 (60.00 Byte)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

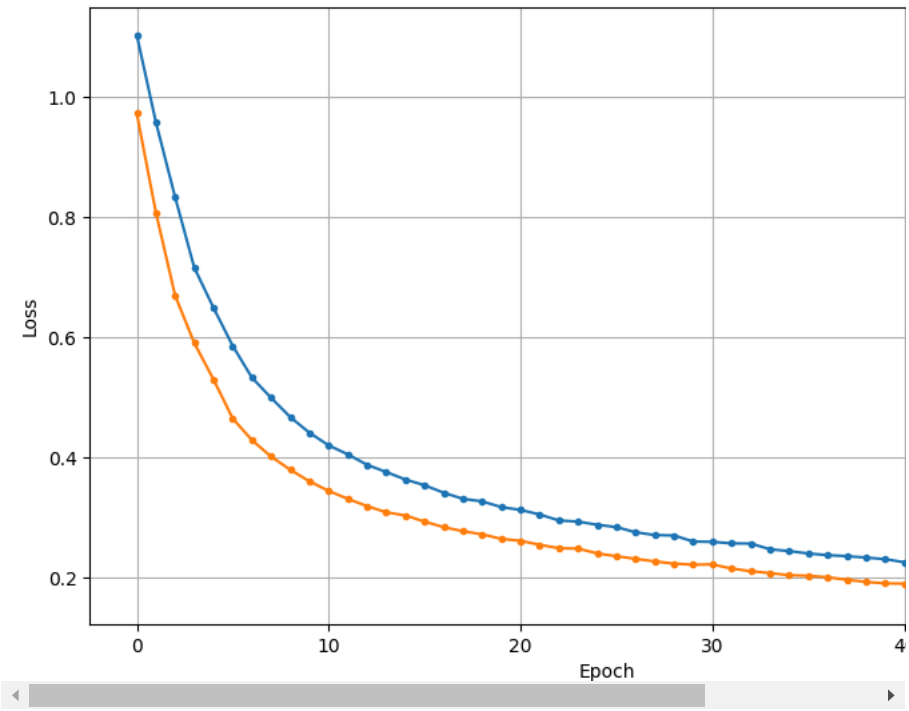
(2) compile + 학습

```
model.compile(optimizer=Adam(learning_rate=0.1), loss= 'sparse_categorical_crossentropy')

history = model.fit(x_train, y_train, epochs = 50, validation_split=0.2).history
```

```
Epoch 37/50
3/3 [==============================] - 0s 46ms/step - loss: 0.2369 - val_loss: 0.1999
Epoch 38/50
3/3 [==============================] - 0s 23ms/step - loss: 0.2351 - val_loss: 0.1958
Epoch 39/50
3/3 [==============================] - 0s 20ms/step - loss: 0.2328 - val_loss: 0.1922
Epoch 40/50
3/3 [==============================] - 0s 18ms/step - loss: 0.2301 - val_loss: 0.1898
Epoch 41/50
3/3 [==============================] - 0s 24ms/step - loss: 0.2250 - val_loss: 0.1893
Epoch 42/50
3/3 [==============================] - 0s 72ms/step - loss: 0.2226 - val_loss: 0.1860
Epoch 43/50
3/3 [==============================] - 0s 33ms/step - loss: 0.2201 - val_loss: 0.1828
Epoch 44/50
3/3 [==============================] - 0s 58ms/step - loss: 0.2157 - val_loss: 0.1807
Epoch 45/50
3/3 [==============================] - 0s 23ms/step - loss: 0.2127 - val_loss: 0.1791
Epoch 46/50
3/3 [==============================] - 0s 47ms/step - loss: 0.2109 - val_loss: 0.1774
Epoch 47/50
3/3 [==============================] - 0s 21ms/step - loss: 0.2096 - val_loss: 0.1746
Epoch 48/50
3/3 [==============================] - 0s 19ms/step - loss: 0.2063 - val_loss: 0.1726
Epoch 49/50
3/3 [==============================] - 0s 14ms/step - loss: 0.2050 - val_loss: 0.1703
Epoch 50/50
3/3 [==============================] - 0s 17ms/step - loss: 0.2026 - val_loss: 0.1690
```

- 학습결과 그래프

```
dl_history_plot(history)
```



(3) 예측 및 검증

- 예측 결과는 softmax로 변환된 값 입니다.

```
pred = model.predict(x_val)
pred[:5]
```

```
2/2 [==============================] - 0s 3ms/step
array([[9.7731495e-01, 2.2585219e-02, 9.9889716e-05],
       [1.1663581e-02, 7.8726929e-01, 2.0106708e-01],
       [1.3979829e-02, 7.1537173e-01, 2.7064845e-01],
       [4.3419775e-04, 3.3963874e-01, 6.5992707e-01],
       [3.5205338e-02, 8.7521440e-01, 8.9580312e-02]], dtype=float32)
```

- 행 별로 제일 큰 값을 찾아서 그에 맞게 숫자(0,1,2)로 변환 합시다.

```
# 5개 행만 살펴보면
np.argmax(pred[:5], axis = 1)
```

```
array([0, 1, 1, 2, 1])
```

```
# 전체에 적용해서 변환합시다.
pred_1 = pred.argmax(axis=1)  # 열에서 가장 큰 값의 인덱스를 1로 반환 나머지는 0으로 반환
pred_1
```

```
array([0, 1, 1, 2, 1, 1, 2, 0, 2, 0, 2, 1, 1, 0, 0, 2, 0, 1, 2, 1, 1, 2,
       2, 0, 1, 1, 1, 0, 2, 1, 1, 1, 0, 0, 0, 1, 2, 0, 1, 2, 1, 1, 0, 1,
       2])
```

- 실제값 y_val은 0,1,2 로 된 1차원 값입니다.

```
y_val
```

```
47     0
73     1
74     1
129    2
67     1
89     1
143    2
21     0
108    2
12     0
147    2
76     1
119    2
35     0
28     0
122    2
13     0
58     1
114    2
57     1
50     1
149    2
111    2
20     0
72     1
81     1
98     1
34     0
104    2
133    2
95     1
88     1
0      0
46     0
11     0
106    2
85     1
1      0
51     1
130    2
55     1
134    2
37     0
65     1
56     1
Name: Species, dtype: int64
```

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

```
[[13  0  0]
 [ 0 16  2]
 [ 0  4 10]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        13
           1       0.80      0.89      0.84        18
           2       0.83      0.71      0.77        14
```

```
           accuracy                           0.87        45
          macro avg       0.88      0.87      0.87        45
       weighted avg       0.87      0.87      0.87        45
```

4.모델링2 : hidden layer

(1) 모델1

- 다음의 summary를 보고 모델을 설계하시오.

Layer (type)	Output Shape	Param #	옵션
dense (Dense)	(None, 8)	40	node, input_shape, activation = 'relu'
dense_1 (Dense)	(None, 3)	27	node, activation = 'softmax'

```
# 메모리 정리
clear_session()

# Sequential 타입 모델 선언
model = Sequential([Dense(8 , input_shape = (nfeatures,), activation = 'relu'),
                    Dense(3 , activation = 'softmax')
])

# 모델요약
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 8)                 40

 dense_1 (Dense)             (None, 3)                 27

=================================================================
Total params: 67 (268.00 Byte)
Trainable params: 67 (268.00 Byte)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

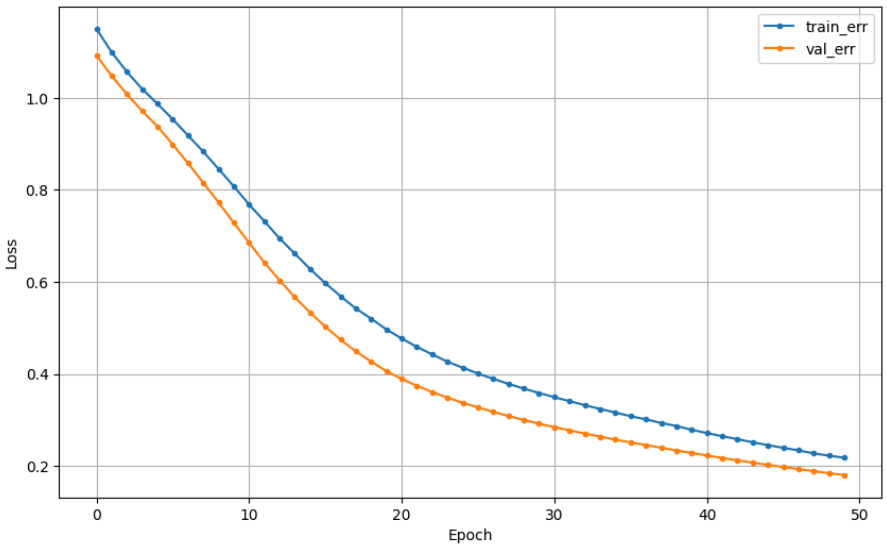
- compile + 학습

```
model.compile(optimizer=Adam(learning_rate=0.01), loss= 'sparse_categorical_crossentropy')

history = model.fit(x_train, y_train, epochs = 50, validation_split=0.2).history
```

```
3/3 [==============================] - 0s 16ms/step - loss: 0.3242 - val_loss: 0.2640
Epoch 35/50
3/3 [==============================] - 0s 16ms/step - loss: 0.3163 - val_loss: 0.2575
Epoch 36/50
3/3 [==============================] - 0s 17ms/step - loss: 0.3084 - val_loss: 0.2513
Epoch 37/50
3/3 [==============================] - 0s 15ms/step - loss: 0.3015 - val_loss: 0.2456
Epoch 38/50
3/3 [==============================] - 0s 15ms/step - loss: 0.2937 - val_loss: 0.2398
Epoch 39/50
3/3 [==============================] - 0s 15ms/step - loss: 0.2871 - val_loss: 0.2340
Epoch 40/50
3/3 [==============================] - 0s 13ms/step - loss: 0.2789 - val_loss: 0.2284
Epoch 41/50
3/3 [==============================] - 0s 13ms/step - loss: 0.2717 - val_loss: 0.2229
Epoch 42/50
3/3 [==============================] - 0s 23ms/step - loss: 0.2649 - val_loss: 0.2175
Epoch 43/50
3/3 [==============================] - 0s 13ms/step - loss: 0.2586 - val_loss: 0.2124
Epoch 44/50
3/3 [==============================] - 0s 13ms/step - loss: 0.2516 - val_loss: 0.2074
Epoch 45/50
3/3 [==============================] - 0s 15ms/step - loss: 0.2455 - val_loss: 0.2026
Epoch 46/50
3/3 [==============================] - 0s 14ms/step - loss: 0.2395 - val_loss: 0.1978
Epoch 47/50
3/3 [==============================] - 0s 15ms/step - loss: 0.2342 - val_loss: 0.1933
Epoch 48/50
3/3 [==============================] - 0s 12ms/step - loss: 0.2275 - val_loss: 0.1889
Epoch 49/50
3/3 [==============================] - 0s 13ms/step - loss: 0.2226 - val_loss: 0.1844
Epoch 50/50
3/3 [==============================] - 0s 17ms/step - loss: 0.2180 - val_loss: 0.1805
```

- 학습결과 그래프

```
dl_history_plot(history)
```



- 예측 및 검증
  - 예측 결과는 softmax로 변환된 값 입니다.

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

```
2/2 [==============================] - 0s 5ms/step
```

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

```
[[13  0  0]
 [ 0 17  1]
 [ 0  3 11]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        13
           1       0.85      0.94      0.89        18
           2       0.92      0.79      0.85        14

    accuracy                           0.91        45
   macro avg       0.92      0.91      0.91        45
weighted avg       0.91      0.91      0.91        45
```

(2) 모델2

- 다음의 summary를 보고 모델을 설계하시오.

Layer (type)	Output Shape	Param #	옵션
dense (Dense)	(None, 8)	40	node, input_shape, activation = 'relu'
dense_1 (Dense)	(None, 8)	72	node, activation = 'relu'
dense_2 (Dense)	(None, 3)	27	node, activation = 'softmax'

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

```
4
```

```
clear_session()
model2 = Sequential([Dense(8, input_shape=(n, ), activation='relu'),
                     Dense(8, activation='relu'),
                     Dense(3, activation='softmax')])
model2.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 8)                 40

 dense_1 (Dense)             (None, 8)                 72

 dense_2 (Dense)             (None, 3)                 27

=================================================================
Total params: 139 (556.00 Byte)
Trainable params: 139 (556.00 Byte)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

- compile + 학습

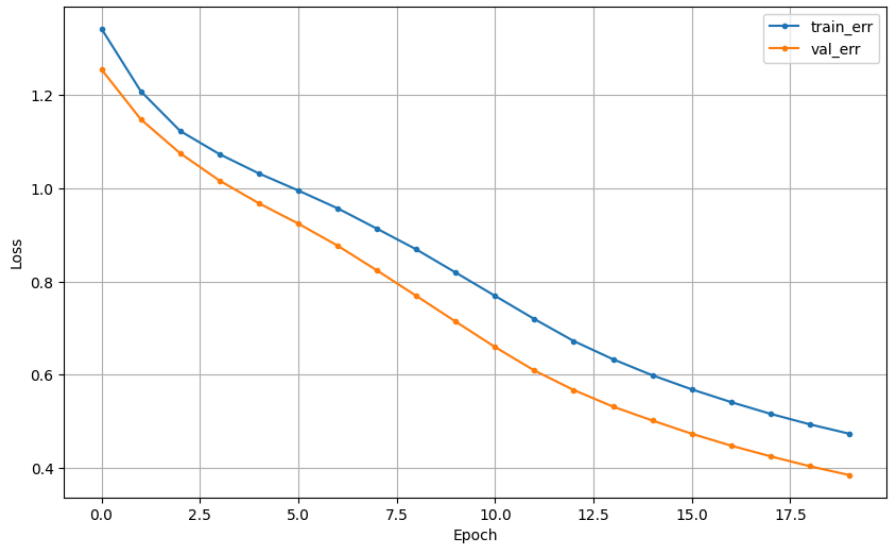
```
model2.compile(optimizer=Adam(0.01), loss='sparse_categorical_crossentropy')
hist = model2.fit(x_train, y_train, epochs=20, validation_split=.2).history
```

```
Epoch 1/20
3/3 [==============================] - 2s 249ms/step - loss: 1.3427 - val_loss: 1.2554
Epoch 2/20
3/3 [==============================] - 0s 39ms/step - loss: 1.2085 - val_loss: 1.1483
Epoch 3/20
3/3 [==============================] - 0s 38ms/step - loss: 1.1232 - val_loss: 1.0754
Epoch 4/20
3/3 [==============================] - 0s 44ms/step - loss: 1.0735 - val_loss: 1.0168
Epoch 5/20
3/3 [==============================] - 0s 34ms/step - loss: 1.0321 - val_loss: 0.9681
Epoch 6/20
3/3 [==============================] - 0s 50ms/step - loss: 0.9956 - val_loss: 0.9246
Epoch 7/20
3/3 [==============================] - 0s 42ms/step - loss: 0.9573 - val_loss: 0.8772
Epoch 8/20
3/3 [==============================] - 0s 49ms/step - loss: 0.9136 - val_loss: 0.8241
Epoch 9/20
3/3 [==============================] - 0s 65ms/step - loss: 0.8691 - val_loss: 0.7694
Epoch 10/20
3/3 [==============================] - 0s 36ms/step - loss: 0.8195 - val_loss: 0.7142
```

```
Epoch 11/20
3/3 [==============================] - 0s 36ms/step - loss: 0.7695 - val_loss: 0.6598
Epoch 12/20
3/3 [==============================] - 0s 46ms/step - loss: 0.7197 - val_loss: 0.6093
Epoch 13/20
3/3 [==============================] - 0s 97ms/step - loss: 0.6726 - val_loss: 0.5675
Epoch 14/20
3/3 [==============================] - 0s 88ms/step - loss: 0.6334 - val_loss: 0.5319
Epoch 15/20
3/3 [==============================] - 0s 82ms/step - loss: 0.5991 - val_loss: 0.5021
Epoch 16/20
3/3 [==============================] - 0s 70ms/step - loss: 0.5689 - val_loss: 0.4737
Epoch 17/20
3/3 [==============================] - 0s 39ms/step - loss: 0.5415 - val_loss: 0.4481
Epoch 18/20
3/3 [==============================] - 0s 43ms/step - loss: 0.5164 - val_loss: 0.4253
Epoch 19/20
3/3 [==============================] - 0s 30ms/step - loss: 0.4939 - val_loss: 0.4040
Epoch 20/20
3/3 [==============================] - 0s 26ms/step - loss: 0.4738 - val_loss: 0.3851
```

- 학습결과 그래프

```
dl_history_plot(hist)
```



- 예측 및 검증
  - 예측 결과는 softmax로 변환된 값 입니다.

```
pred = model2.predict(x_val)
pred = np.argmax(pred, axis=1)
```

```
2/2 [==============================] - 0s 4ms/step
```

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

```
[13  0  0]
[ 0  0 18]
[ 0  0 14]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        13
           1       0.00      0.00      0.00        18
           2       0.44      1.00      0.61        14

    accuracy                           0.60        45
   macro avg       0.48      0.67      0.54        45
```

```
eighted avg       0.42      0.60      0.48        45

usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and beir
  _warn_prf(average, modifier, msg_start, len(result))
usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and beir
  _warn_prf(average, modifier, msg_start, len(result))
usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-defined and beir
  _warn_prf(average, modifier, msg_start, len(result))
```

(3) 모델3

- 여러분이 원하는 형태로 설계를 해 봅시다.

```
n
```

```
4
```

```
clear_session()
model3 = Sequential([Dense(16, input_shape=(n,), activation='relu'),
                     Dense(9, activation='relu'),
                     Dense(3, activation='softmax'),])
model3.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 16)                80

 dense_1 (Dense)             (None, 9)                 153

 dense_2 (Dense)             (None, 3)                 30

=================================================================
Total params: 263 (1.03 KB)
Trainable params: 263 (1.03 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

- compile + 학습

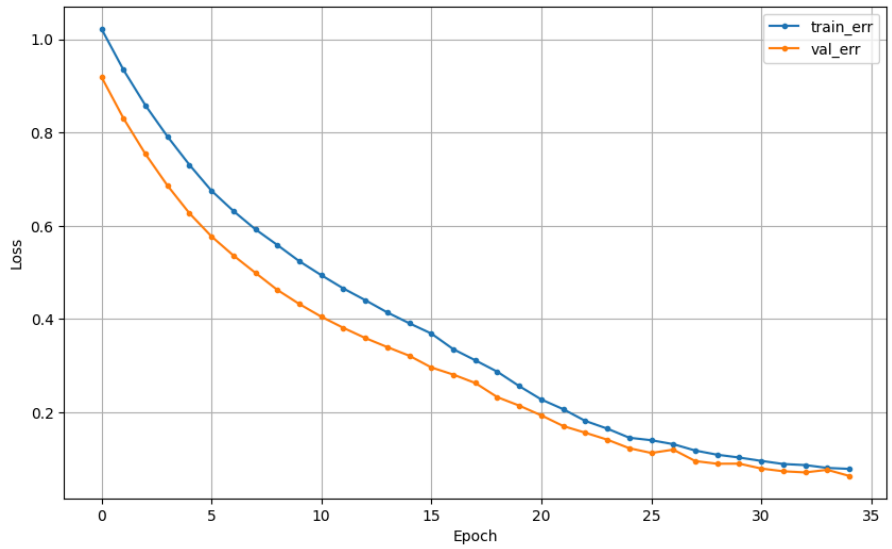
```
model3.compile(optimizer=Adam(0.01), loss='sparse_categorical_crossentropy')
hist = model3.fit(x_train, y_train, epochs=35, validation_split=.2).history # verbose = 0
```

```
Epoch 7/35
3/3 [==============================] - 0s 16ms/step - loss: 0.6318 - val_loss: 0.5365
Epoch 8/35
3/3 [==============================] - 0s 15ms/step - loss: 0.5926 - val_loss: 0.4993
Epoch 9/35
3/3 [==============================] - 0s 19ms/step - loss: 0.5588 - val_loss: 0.4626
Epoch 10/35
3/3 [==============================] - 0s 14ms/step - loss: 0.5240 - val_loss: 0.4323
Epoch 11/35
3/3 [==============================] - 0s 15ms/step - loss: 0.4941 - val_loss: 0.4051
Epoch 12/35
3/3 [==============================] - 0s 15ms/step - loss: 0.4657 - val_loss: 0.3813
Epoch 13/35
3/3 [==============================] - 0s 14ms/step - loss: 0.4406 - val_loss: 0.3594
Epoch 14/35
3/3 [==============================] - 0s 16ms/step - loss: 0.4143 - val_loss: 0.3400
Epoch 15/35
3/3 [==============================] - 0s 14ms/step - loss: 0.3911 - val_loss: 0.3215
Epoch 16/35
```

```
3/3 [==============================] - 0s 15ms/step - loss: 0.2068 - val_loss: 0.1707
Epoch 23/35
3/3 [==============================] - 0s 14ms/step - loss: 0.1818 - val_loss: 0.1564
Epoch 24/35
3/3 [==============================] - 0s 13ms/step - loss: 0.1652 - val_loss: 0.1416
Epoch 25/35
3/3 [==============================] - 0s 14ms/step - loss: 0.1457 - val_loss: 0.1233
Epoch 26/35
3/3 [==============================] - 0s 15ms/step - loss: 0.1404 - val_loss: 0.1131
Epoch 27/35
3/3 [==============================] - 0s 15ms/step - loss: 0.1320 - val_loss: 0.1202
Epoch 28/35
3/3 [==============================] - 0s 14ms/step - loss: 0.1183 - val_loss: 0.0957
Epoch 29/35
3/3 [==============================] - 0s 15ms/step - loss: 0.1093 - val_loss: 0.0900
Epoch 30/35
3/3 [==============================] - 0s 13ms/step - loss: 0.1032 - val_loss: 0.0902
Epoch 31/35
3/3 [==============================] - 0s 14ms/step - loss: 0.0961 - val_loss: 0.0797
Epoch 32/35
3/3 [==============================] - 0s 14ms/step - loss: 0.0894 - val_loss: 0.0738
Epoch 33/35
3/3 [==============================] - 0s 13ms/step - loss: 0.0871 - val_loss: 0.0714
Epoch 34/35
3/3 [==============================] - 0s 13ms/step - loss: 0.0811 - val_loss: 0.0769
Epoch 35/35
3/3 [==============================] - 0s 19ms/step - loss: 0.0790 - val_loss: 0.0639
```

- 학습결과 그래프

```
dl_history_plot(hist)
```



- 예측 및 검증
  - 예측 결과는 softmax로 변환된 값 입니다.

```
pred = model3.predict(x_val)
pred = np.argmax(pred, axis=1)
```

```
2/2 [==============================] - 0s 5ms/step
```

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

```
[[13  0  0]
 [ 0 17  1]
 [ 0  3 11]]
              precision    recall  f1-score   support
```

```
                0       1.00      1.00      1.00        13
                1       0.85      0.94      0.89        18
                2       0.92      0.79      0.85        14

         accuracy                           0.91        45
        macro avg       0.92      0.91      0.91        45
     weighted avg       0.91      0.91      0.91        45
```

5.참조 : y를 one-hot encoding 하여 모델링

- y 가변수화 : to_categorical
- 컴파일에서 loss = 'categorical_crossentropy'

```
from keras.utils import to_categorical
```

(1) y에 대한 가변수화

```
y
```

```
0      0
1      0
2      0
3      0
4      0
      ..
145    2
146    2
147    2
148    2
149    2
Name: Species, Length: 150, dtype: int64
```

```
y_c = to_categorical(y.values, 3) # 클래스 3개 원-핫-인코딩
```

```
y_c[:5]
```

```
array([[1., 0., 0.],
       [1., 0., 0.],
       [1., 0., 0.],
       [1., 0., 0.],
       [1., 0., 0.]], dtype=float32)
```

```
y_c[-5:]
```

```
array([[0., 0., 1.],
       [0., 0., 1.],
       [0., 0., 1.],
       [0., 0., 1.],
       [0., 0., 1.]], dtype=float32)
```

(2) 데이터 분할2 : train : val

```
x_train, x_val, y_train, y_val = train_test_split(x, y_c, test_size = .2, random_state = 2024)
```

```
y_train.shape
```

```
(120, 3)
```

(3) Scaling

```
scaler = MinMaxScaler()
x_train = scaler.fit_transform(x_train)
x_val = scaler.transform(x_val)
```

(4) 모델 설계

```
nfeatures = x_train.shape[1] #num of columns
nfeatures
```

```
4
```

```
# 메모리 정리
clear_session()

# Sequential
model = Sequential([Dense(3, input_shape = (nfeatures,), activation = 'softmax')])

# 모델요약
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 3)                 15

=================================================================
Total params: 15 (60.00 Byte)
Trainable params: 15 (60.00 Byte)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

(5) compile + 학습

- lr과 learning_rate은 같은 의미 입니다. 그러나 향후 버전에서는 lr이 제외될 예정이라고 합니다.
- y를 one-hot encoding 했다면, loss fuction은 **categorical_crossentropy** 입니다.

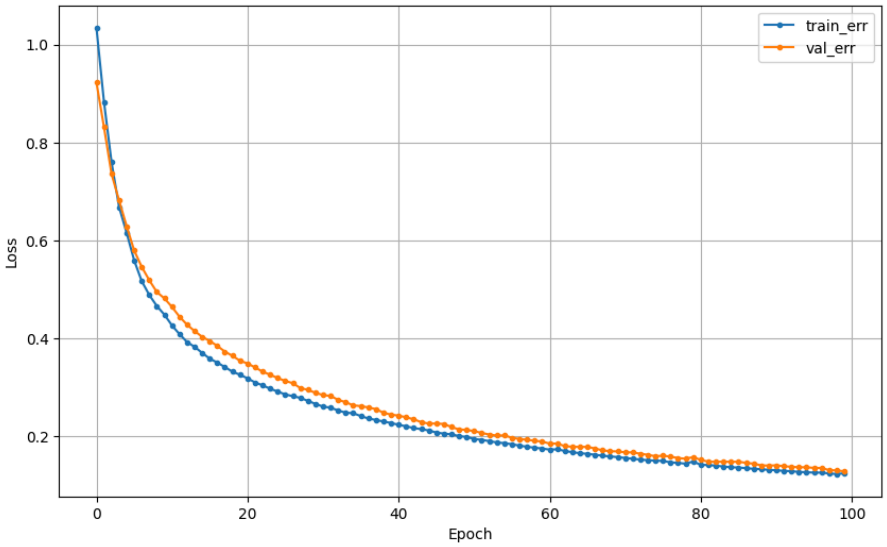
```
model.compile(optimizer=Adam(learning_rate=0.1), loss='categorical_crossentropy')

history = model.fit(x_train, y_train, epochs = 100,
                    validation_split=0.2).history
```

```
Epoch 1/100
3/3 [==============================] - 1s 94ms/step - loss: 1.0344 - val_loss: 0.9226
Epoch 2/100
3/3 [==============================] - 0s 16ms/step - loss: 0.8830 - val_loss: 0.8314
Epoch 3/100
3/3 [==============================] - 0s 17ms/step - loss: 0.7601 - val_loss: 0.7359
Epoch 4/100
3/3 [==============================] - 0s 18ms/step - loss: 0.6683 - val_loss: 0.6816
Epoch 5/100
3/3 [==============================] - 0s 17ms/step - loss: 0.6155 - val_loss: 0.6292
Epoch 6/100
3/3 [==============================] - 0s 29ms/step - loss: 0.5593 - val_loss: 0.5794
Epoch 7/100
3/3 [==============================] - 0s 22ms/step - loss: 0.5169 - val_loss: 0.5460
Epoch 8/100
3/3 [==============================] - 0s 20ms/step - loss: 0.4887 - val_loss: 0.5188
Epoch 9/100
3/3 [==============================] - 0s 23ms/step - loss: 0.4662 - val_loss: 0.4948
Epoch 10/100
3/3 [==============================] - 0s 19ms/step - loss: 0.4486 - val_loss: 0.4819
Epoch 11/100
3/3 [==============================] - 0s 26ms/step - loss: 0.4267 - val_loss: 0.4645
Epoch 12/100
3/3 [==============================] - 0s 18ms/step - loss: 0.4088 - val_loss: 0.4444
Epoch 13/100
3/3 [==============================] - 0s 17ms/step - loss: 0.3928 - val_loss: 0.4282
Epoch 14/100
3/3 [==============================] - 0s 29ms/step - loss: 0.3829 - val_loss: 0.4150
Epoch 15/100
3/3 [==============================] - 0s 23ms/step - loss: 0.3706 - val_loss: 0.4034
Epoch 16/100
3/3 [==============================] - 0s 28ms/step - loss: 0.3588 - val_loss: 0.3949
Epoch 17/100
3/3 [==============================] - 0s 20ms/step - loss: 0.3508 - val_loss: 0.3849
Epoch 18/100
3/3 [==============================] - 0s 25ms/step - loss: 0.3416 - val_loss: 0.3733
Epoch 19/100
3/3 [==============================] - 0s 21ms/step - loss: 0.3324 - val_loss: 0.3646
```

```
Epoch 20/100
3/3 [==============================] - 0s 25ms/step - loss: 0.3260 - val_loss: 0.3547
Epoch 21/100
3/3 [==============================] - 0s 20ms/step - loss: 0.3187 - val_loss: 0.3491
Epoch 22/100
3/3 [==============================] - 0s 19ms/step - loss: 0.3103 - val_loss: 0.3410
Epoch 23/100
3/3 [==============================] - 0s 15ms/step - loss: 0.3044 - val_loss: 0.3322
Epoch 24/100
3/3 [==============================] - 0s 15ms/step - loss: 0.2975 - val_loss: 0.3261
Epoch 25/100
3/3 [==============================] - 0s 15ms/step - loss: 0.2917 - val_loss: 0.3192
Epoch 26/100
3/3 [==============================] - 0s 15ms/step - loss: 0.2858 - val_loss: 0.3133
Epoch 27/100
3/3 [==============================] - 0s 12ms/step - loss: 0.2823 - val_loss: 0.3088
Epoch 28/100
3/3 [==============================] - 0s 14ms/step - loss: 0.2787 - val_loss: 0.2988
Epoch 29/100
3/3 [==============================] - 0s 13ms/step - loss: 0.2726 - val_loss: 0.2952
```

- 학습결과 그래프

```
dl_history_plot(history)
```



(6) 예측 및 평가

- 예측 결과는 softmax로 변환된 값 입니다.

```
pred = model.predict(x_val)
pred[:5]
```

```
1/1 [==============================] - 0s 49ms/step
array([[9.9677032e-01, 3.2295987e-03, 7.3899380e-09],
       [9.9682307e-01, 3.1769781e-03, 9.6102788e-09],
       [4.1914028e-03, 7.6582640e-01, 2.2998214e-01],
       [1.3650069e-03, 4.4500309e-01, 5.5363190e-01],
       [9.9673170e-01, 3.2682274e-03, 1.4031255e-08]], dtype=float32)
```

- 행 별로 제일 큰 값을 찾아서 그에 맞게 숫자(0,1,2)로 변환 합시다.

```
# 5개 행만 살펴보면
np.argmax(pred[:5], axis = 1)
```

```
array([0, 0, 1, 2, 0])
```

```
y_val
```

```
array([[1., 0., 0.],
       [1., 0., 0.],
       [0., 1., 0.],
       [0., 0., 1.],
       [1., 0., 0.],
       [0., 1., 0.],
       [0., 1., 0.],
       [0., 0., 1.],
       [1., 0., 0.],
       [1., 0., 0.],
       [0., 1., 0.],
       [0., 0., 1.],
       [1., 0., 0.],
       [1., 0., 0.],
       [0., 1., 0.],
       [0., 0., 1.],
       [1., 0., 0.],
       [0., 0., 1.],
       [1., 0., 0.],
       [0., 1., 0.],
       [0., 1., 0.],
       [0., 0., 1.],
       [0., 0., 1.],
       [0., 1., 0.],
       [1., 0., 0.],
       [0., 0., 1.],
       [0., 0., 1.],
       [1., 0., 0.],
       [0., 0., 1.],
       [1., 0., 0.]], dtype=float32)
```

```
# 전체에 적용해서 변환합시다.
pred_1 = pred.argmax(axis=1)
pred_1
```

```
array([0, 0, 1, 2, 0, 1, 1, 2, 0, 0, 2, 2, 0, 0, 1, 2, 0, 1, 0, 1, 1, 2,
       2, 2, 0, 2, 2, 0, 2, 0])
```

- 실제값 y_val도 원래 대로 돌려 놓습니다.

```
y_val[:5]
```

```
array([[1., 0., 0.],
       [1., 0., 0.],
       [0., 1., 0.],
       [0., 0., 1.],
       [1., 0., 0.]], dtype=float32)
```

```
y_val_1 = y_val.argmax(axis=1)
y_val_1
```

```
array([0, 0, 1, 2, 0, 1, 1, 2, 0, 0, 1, 2, 0, 0, 1, 2, 0, 2, 0, 1, 1, 2,
       2, 1, 0, 2, 2, 0, 2, 0])
```

```
print(confusion_matrix(y_val_1, pred_1))
print(classification_report(y_val_1, pred_1))
```

```
[[12  0  0]
 [ 0  6  2]
 [ 0  1  9]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        12
           1       0.86      0.75      0.80         8
           2       0.82      0.90      0.86        10

    accuracy                           0.90        30
   macro avg       0.89      0.88      0.89        30
weighted avg       0.90      0.90      0.90        30
```

코딩을 시작하거나 AI로 코드를 생성하세요.