#Nile Pallavi Roll NO: 4217 Div:B
 # DL Practical NO.2

```
import pandas as pd
import numpy as np

df = pd.read_csv(r'C:\Users\Pallavi Nile\Downloads\DL\pract_2\letter-recognition.csv')
print(df)
columns = ["letter", "x-box", "y-box", "width", "height", "onpix", "x-bar",
"y-bar", "x2bar", "y2bar", "xybar", "x2ybr", "xy2br", "x-ege", "xegvy",
"y-ege", "yegvx"]
x = df.drop("letter", axis=1).values
y = df["letter"].values
print("shape of x")
print(x.shape)
print("shape of y")
print(y.shape)
print(np.unique(y))

# Split the data into training and testing sets
test_size = 0.2  # Percentage of data to be used for testing
num_test_samples = int(test_size * len(df))

# Shuffle the indices of the data randomly
shuffled_indices = np.random.permutation(len(df))

# Split the indices into training and test sets
test_indices = shuffled_indices[:num_test_samples]
train_indices = shuffled_indices[num_test_samples:]

# Split the features and target variable based on the indices
x_train = x[train_indices]
x_test = x[test_indices]
y_train = y[train_indices]
y_test = y[test_indices]

print("Shape of x_train:", x_train.shape)
print("Shape of x_test:", x_test.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)

print(x_train[0])
```

```
print(y_train[0])

class_names=['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J', 'K', 'L', 'M','N', 'O', 'P', 'Q', 'R', 'S', 'T', 'U', 'V', 'W', 'X', 'Y',
'Z']
print(x_test[10])
print(y_test[10])

#preprocessing step

x_train = x_train/255
x_test = x_test/255
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
y_train = encoder.fit_transform(y_train)
y_test = encoder.fit_transform(y_test)

#model building

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
model=Sequential()
model.add(Dense(512, activation='relu', input_shape=(16,)))
model.add(Dropout(0.2))
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(26, activation='softmax'))
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
model.summary()

#model training
model.fit(x_train, y_train, epochs=50, batch_size=128, verbose=1,validation_data=(x_test, y_test))

#testing model
predictions = model.predict(x_test)
index=10
print(predictions[index])
final_value=np.argmax(predictions[index])
print("Actual label :",y_test[index])
print("Predicted label :",final_value)
print("Class (A-Z) :",class_names[final_value])
```

```
#model Evaluation

loss, accuracy = model.evaluate(x_test, y_test)
print("Loss :",loss)
print("Accuracy (Test Data) :",accuracy*100)
```

Output:

```
    letter  xbox   ybox   width   ...  xedge   xedgey  yedge   yedgex
0        T     2     8      3  ...      0      8      0      8
1        I     5    12      3  ...      2      8      4     10
2        D     4    11      6  ...      3      7      3      9
3        N     7    11      6  ...      6     10      2      8
4        G     2     1      3  ...      1      7      5     10
    ...   ...   ...   ...  ...    ...    ...    ...    ...
19995    D     2     2      3  ...      2      8      3      7
19996    C     7    10      8  ...      2      9      3      7
19997    T     6     9      6  ...      2     12      2      4
19998    S     2     3      4  ...      1      9      5      8
19999    A     4     9      6  ...      2      7      2      8

[20000 rows x 17 columns]
shape of x
(20000, 16)
shape of y
(20000,)
['A' 'B' 'C' 'D' 'E' 'F' 'G' 'H' 'I' 'J' 'K' 'L' 'M' 'N' 'O' 'P' 'Q' 'R'
 'S' 'T' 'U' 'V' 'W' 'X' 'Y' 'Z']
Shape of x_train: (16000, 16)
Shape of x_test: (4000, 16)
Shape of y_train: (16000,)
Shape of y_test: (4000,)
[4 6 6 5 5 7 7 4 4 6 5 8 6 8 4 6]
N
[1 3 1 2 0 7 7 1 8 7 6 8 0 8 3 8]
I
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 512)               8704
```

```
 dropout (Dropout)          (None, 512)            0

 dense_1 (Dense)            (None, 256)            131328

 dropout_1 (Dropout)        (None, 256)            0

 dense_2 (Dense)            (None, 26)             6682

=================================================================
Total params: 146,714
Trainable params: 146,714
Non-trainable params: 0
_________________________________________________________________
Epoch 1/50
125/125 [==============================] - 1s 7ms/step - loss: 3.1287 - accuracy: 0.1683 - val_loss:
2.7543 - val_accuracy: 0.3203
Epoch 2/50
125/125 [==============================] - 1s 6ms/step - loss: 2.3519 - accuracy: 0.3257 - val_loss:
2.0490 - val_accuracy: 0.4112
Epoch 3/50
125/125 [==============================] - 1s 6ms/step - loss: 1.9355 - accuracy: 0.4156 - val_loss:
1.7457 - val_accuracy: 0.4885
Epoch 4/50
125/125 [==============================] - 1s 6ms/step - loss: 1.7040 - accuracy: 0.4884 - val_loss:
1.5754 - val_accuracy: 0.5428
Epoch 5/50
125/125 [==============================] - 1s 5ms/step - loss: 1.5696 - accuracy: 0.5303 - val_loss:
1.4665 - val_accuracy: 0.5705
Epoch 6/50
125/125 [==============================] - 1s 6ms/step - loss: 1.4787 - accuracy: 0.5598 - val_loss:
1.3805 - val_accuracy: 0.6037
Epoch 7/50
125/125 [==============================] - 1s 7ms/step - loss: 1.4022 - accuracy: 0.5866 - val_loss:
1.3334 - val_accuracy: 0.6125
Epoch 8/50
125/125 [==============================] - 1s 6ms/step - loss: 1.3565 - accuracy: 0.5974 - val_loss:
1.2783 - val_accuracy: 0.6315
Epoch 9/50
125/125 [==============================] - 1s 5ms/step - loss: 1.2979 - accuracy: 0.6168 - val_loss:
1.2290 - val_accuracy: 0.6345
Epoch 10/50
```

125/125 [==============================] - 1s 6ms/step - loss: 1.2422 - accuracy: 0.6357 - val_loss: 1.1690 - val_accuracy: 0.6718
Epoch 11/50
125/125 [==============================] - 1s 6ms/step - loss: 1.1950 - accuracy: 0.6498 - val_loss: 1.1155 - val_accuracy: 0.6842
Epoch 12/50
125/125 [==============================] - 1s 5ms/step - loss: 1.1487 - accuracy: 0.6609 - val_loss: 1.0799 - val_accuracy: 0.6938
Epoch 13/50
125/125 [==============================] - 1s 6ms/step - loss: 1.1130 - accuracy: 0.6729 - val_loss: 1.0414 - val_accuracy: 0.6995
Epoch 14/50
125/125 [==============================] - 1s 6ms/step - loss: 1.0716 - accuracy: 0.6819 - val_loss: 1.0016 - val_accuracy: 0.7140
Epoch 15/50
125/125 [==============================] - 1s 6ms/step - loss: 1.0416 - accuracy: 0.6911 - val_loss: 0.9684 - val_accuracy: 0.7172
Epoch 16/50
125/125 [==============================] - 1s 6ms/step - loss: 1.0067 - accuracy: 0.6962 - val_loss: 0.9760 - val_accuracy: 0.7140
Epoch 17/50
125/125 [==============================] - 1s 6ms/step - loss: 0.9810 - accuracy: 0.7078 - val_loss: 0.9111 - val_accuracy: 0.7390
Epoch 18/50
125/125 [==============================] - 1s 6ms/step - loss: 0.9423 - accuracy: 0.7169 - val_loss: 0.8839 - val_accuracy: 0.7427
Epoch 19/50
125/125 [==============================] - 1s 6ms/step - loss: 0.9161 - accuracy: 0.7271 - val_loss: 0.8605 - val_accuracy: 0.7480
Epoch 20/50
125/125 [==============================] - 1s 6ms/step - loss: 0.8934 - accuracy: 0.7290 - val_loss: 0.8480 - val_accuracy: 0.7465
Epoch 21/50
125/125 [==============================] - 1s 6ms/step - loss: 0.8738 - accuracy: 0.7359 - val_loss: 0.8183 - val_accuracy: 0.7632
Epoch 22/50
125/125 [==============================] - 1s 7ms/step - loss: 0.8545 - accuracy: 0.7408 - val_loss: 0.7997 - val_accuracy: 0.7592
Epoch 23/50
125/125 [==============================] - 1s 6ms/step - loss: 0.8356 - accuracy: 0.7479 - val_loss: 0.7805 - val_accuracy: 0.7628
Epoch 24/50

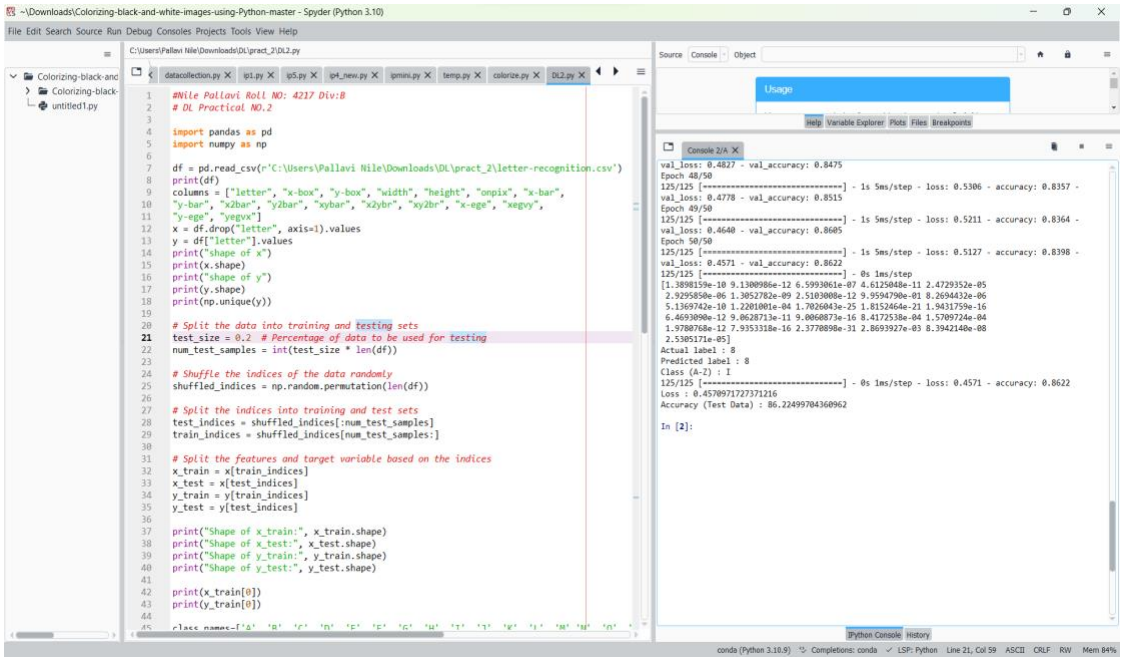
125/125 [==============================] - 1s 7ms/step - loss: 0.8167 - accuracy: 0.7516 - val_loss: 0.7541 - val_accuracy: 0.7747
Epoch 25/50
125/125 [==============================] - 1s 7ms/step - loss: 0.7982 - accuracy: 0.7580 - val_loss: 0.7389 - val_accuracy: 0.7812
Epoch 26/50
125/125 [==============================] - 1s 7ms/step - loss: 0.7831 - accuracy: 0.7637 - val_loss: 0.7354 - val_accuracy: 0.7720
Epoch 27/50
125/125 [==============================] - 1s 6ms/step - loss: 0.7728 - accuracy: 0.7638 - val_loss: 0.7095 - val_accuracy: 0.7912
Epoch 28/50
125/125 [==============================] - 1s 6ms/step - loss: 0.7552 - accuracy: 0.7686 - val_loss: 0.7051 - val_accuracy: 0.7862
Epoch 29/50
125/125 [==============================] - 1s 7ms/step - loss: 0.7402 - accuracy: 0.7725 - val_loss: 0.6894 - val_accuracy: 0.7920
Epoch 30/50
125/125 [==============================] - 1s 6ms/step - loss: 0.7271 - accuracy: 0.7766 - val_loss: 0.6751 - val_accuracy: 0.7918
Epoch 31/50
125/125 [==============================] - 1s 6ms/step - loss: 0.7144 - accuracy: 0.7790 - val_loss: 0.6678 - val_accuracy: 0.7977
Epoch 32/50
125/125 [==============================] - 1s 6ms/step - loss: 0.6950 - accuracy: 0.7866 - val_loss: 0.6394 - val_accuracy: 0.8077
Epoch 33/50
125/125 [==============================] - 1s 6ms/step - loss: 0.6847 - accuracy: 0.7910 - val_loss: 0.6516 - val_accuracy: 0.8010
Epoch 34/50
125/125 [==============================] - 1s 6ms/step - loss: 0.6696 - accuracy: 0.7931 - val_loss: 0.6345 - val_accuracy: 0.8060
Epoch 35/50
125/125 [==============================] - 1s 6ms/step - loss: 0.6600 - accuracy: 0.7968 - val_loss: 0.6001 - val_accuracy: 0.8185
Epoch 36/50
125/125 [==============================] - 1s 5ms/step - loss: 0.6448 - accuracy: 0.8016 - val_loss: 0.5999 - val_accuracy: 0.8170
Epoch 37/50
125/125 [==============================] - 0s 3ms/step - loss: 0.6355 - accuracy: 0.8054 - val_loss: 0.5788 - val_accuracy: 0.8195
Epoch 38/50

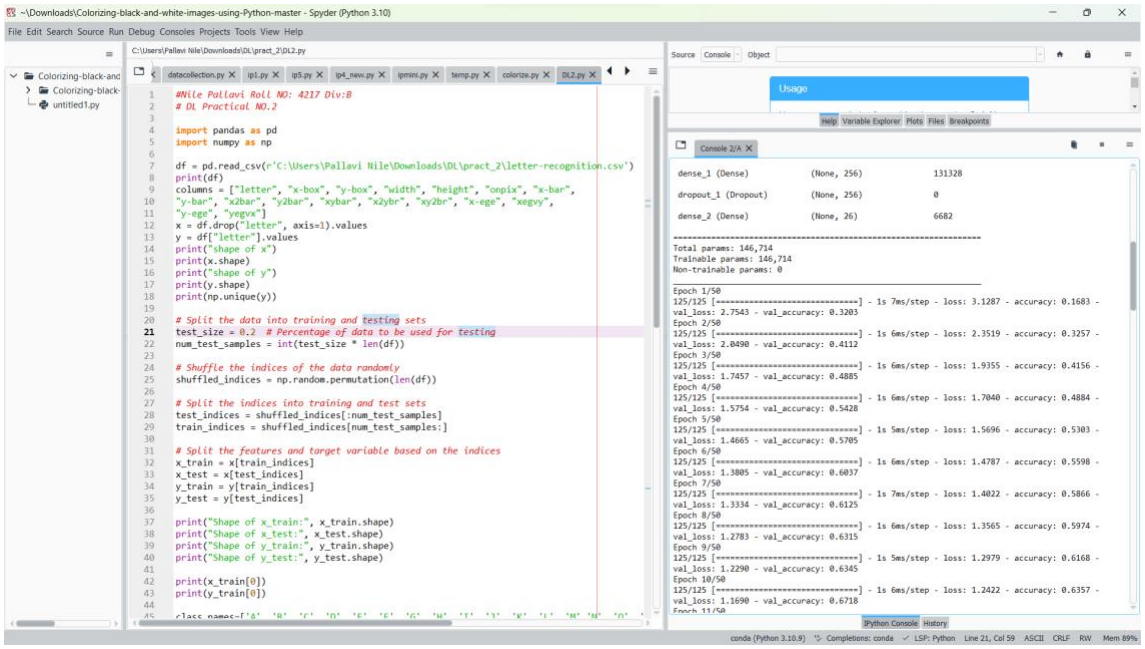
125/125 [==============================] - 0s 4ms/step - loss: 0.6240 - accuracy: 0.8071 - val_loss: 0.5701 - val_accuracy: 0.8255
Epoch 39/50
125/125 [==============================] - 1s 4ms/step - loss: 0.6099 - accuracy: 0.8106 - val_loss: 0.5735 - val_accuracy: 0.8192
Epoch 40/50
125/125 [==============================] - 0s 4ms/step - loss: 0.6054 - accuracy: 0.8142 - val_loss: 0.5661 - val_accuracy: 0.8275
Epoch 41/50
125/125 [==============================] - 0s 4ms/step - loss: 0.5954 - accuracy: 0.8156 - val_loss: 0.5394 - val_accuracy: 0.8322
Epoch 42/50
125/125 [==============================] - 1s 4ms/step - loss: 0.5823 - accuracy: 0.8202 - val_loss: 0.5310 - val_accuracy: 0.8372
Epoch 43/50
125/125 [==============================] - 1s 5ms/step - loss: 0.5741 - accuracy: 0.8206 - val_loss: 0.5314 - val_accuracy: 0.8335
Epoch 44/50
125/125 [==============================] - 1s 4ms/step - loss: 0.5711 - accuracy: 0.8209 - val_loss: 0.5194 - val_accuracy: 0.8382
Epoch 45/50
125/125 [==============================] - 1s 5ms/step - loss: 0.5549 - accuracy: 0.8297 - val_loss: 0.5096 - val_accuracy: 0.8425
Epoch 46/50
125/125 [==============================] - 1s 5ms/step - loss: 0.5517 - accuracy: 0.8314 - val_loss: 0.4934 - val_accuracy: 0.8435
Epoch 47/50
125/125 [==============================] - 1s 5ms/step - loss: 0.5375 - accuracy: 0.8311 - val_loss: 0.4827 - val_accuracy: 0.8475
Epoch 48/50
125/125 [==============================] - 1s 5ms/step - loss: 0.5306 - accuracy: 0.8357 - val_loss: 0.4778 - val_accuracy: 0.8515
Epoch 49/50
125/125 [==============================] - 1s 5ms/step - loss: 0.5211 - accuracy: 0.8364 - val_loss: 0.4640 - val_accuracy: 0.8605
Epoch 50/50
125/125 [==============================] - 1s 5ms/step - loss: 0.5127 - accuracy: 0.8398 - val_loss: 0.4571 - val_accuracy: 0.8622
125/125 [==============================] - 0s 1ms/step

[1.3898159e-10 9.1300986e-12 6.5993061e-07 4.6125048e-11 2.4729352e-05
 2.9295850e-06 1.3052782e-09 2.5103008e-12 9.9594790e-01 8.2694432e-06

5.1369742e-10 1.2201001e-04 1.7026043e-25 1.8152464e-21 1.9431759e-16
6.4693090e-12 9.0628713e-11 9.0060873e-16 8.4172538e-04 1.5709724e-04
1.9780768e-12 7.9353318e-16 2.3770898e-31 2.8693927e-03 8.3942140e-08
2.5305171e-05]

Actual label : 8
Predicted label : 8
Class (A-Z) : I
125/125 [==============================] - 0s 1ms/step - loss: 0.4571 - accuracy: 0.8622
Loss : 0.4570971727371216
Accuracy (Test Data) : 86.22499704360962




~\Downloads\Colorizing-black-and-white-images-using-Python-master - Spyder (Python 3.10)
File Edit Search Source Run Debug Consoles Projects Tools View Help
C:\Users\Pallavi Nile\Downloads\DL\pract_2\DL2.py
datacollection.py
ip1.py
ip5.py
ip4_new.py
ipmini.py
temp.py
colorize.py
DL2.py
Colorizing-black-and
Colorizing-black-
untitled1.py
#Nile Pallavi Roll NO: 4217 Div:B
# DL Practical NO.2
import pandas as pd
import numpy as np
df = pd.read_csv(r'C:\Users\Pallavi Nile\Downloads\DL\pract_2\letter-recognition.csv')
print(df)
columns = ["letter", "x-box", "y-box", "width", "height", "onpix", "x-bar",
"y-bar", "x2bar", "y2bar", "xybar", "x2ybr", "xy2br", "x-ege", "xegvy",
"y-ege", "yegvx"]
x = df.drop("letter", axis=1).values
y = df["letter"].values
print("shape of x")
print(x.shape)
print("shape of y")
print(y.shape)
print(np.unique(y))
# Split the data into training and testing sets
test_size = 0.2 # Percentage of data to be used for testing
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shuffled_indices = np.random.permutation(len(df))
# Split the indices into training and test sets
test_indices = shuffled_indices[:num_test_samples]
train_indices = shuffled_indices[num_test_samples:]
# Split the features and target variable based on the indices
x_train = x[train_indices]
x_test = x[test_indices]
y_train = y[train_indices]
y_test = y[test_indices]
print("Shape of x_train:", x_train.shape)
print("Shape of x_test:", x_test.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)
print(x_train[0])
print(y_train[0])
Source
Console
Object
Usage
Help
Variable Explorer
Plots
Files
Breakpoints
Console 2/A
dense_1 (Dense) (None, 256) 131328
dropout_1 (Dropout) (None, 256) 0
dense_2 (Dense) (None, 26) 6682
Total params: 146,714
Trainable params: 146,714
Non-trainable params: 0
Epoch 1/50
125/125 [==========] - 1s 7ms/step - loss: 3.1287 - accuracy: 0.1683 - val_loss: 2.7543 - val_accuracy: 0.3203
Epoch 2/50
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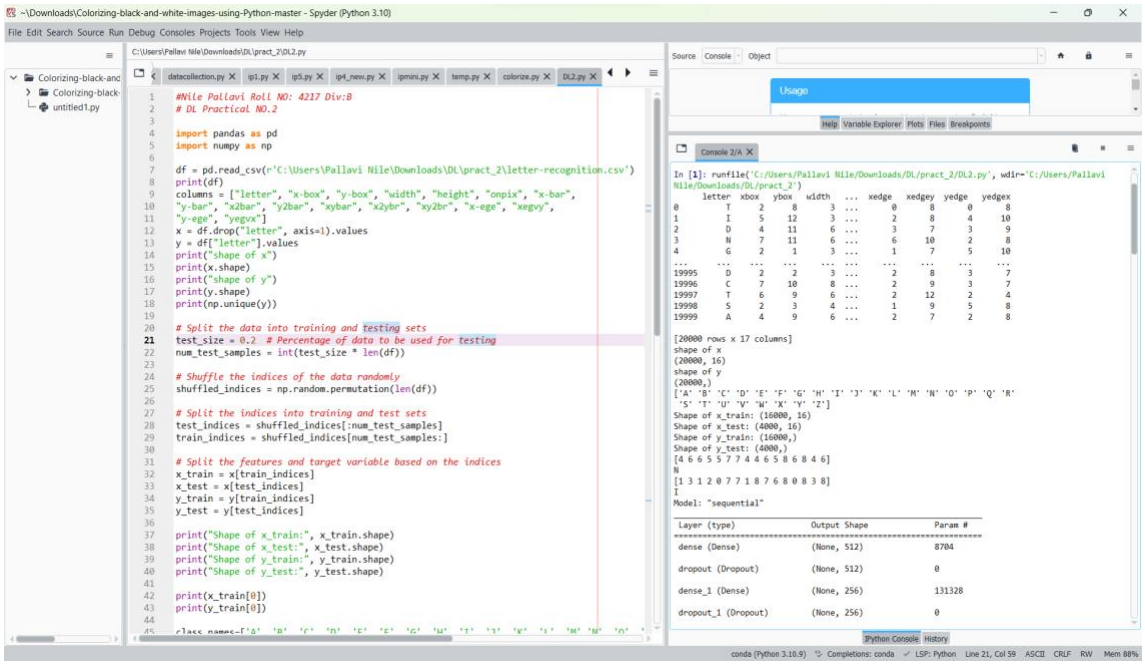
IPython Console
History
conda (Python 3.10.9)
Completions: conda
LSP: Python
Line 21, Col 59
ASCII
CRLF
RW
Mem 89%


~\Downloads\Colorizing-black-and-white-images-using-Python-master - Spyder (Python 3.10)
File Edit Search Source Run Debug Consoles Projects Tools View Help
C:\Users\Pallavi Nile\Downloads\DL\pract_2\DL2.py
#Nile Pallavi Roll NO: 4217 Div:B
# DL Practical NO.2
df = pd.read_csv(r'C:\Users\Pallavi Nile\Downloads\DL\pract_2\letter-recognition.csv')
In [1]: runfile('C:/Users/Pallavi Nile/Downloads/DL/pract_2/DL2.py', wdir='C:/Users/Pallavi Nile/Downloads/DL/pract_2')
letter xbox ybox width ... xedge xedgey yedge yedgex
0 T 2 8 3 ... 0 8 0 8
1 I 5 12 3 ... 2 8 4 10
2 D 4 11 6 ... 3 7 3 9
3 N 7 11 6 ... 6 10 2 8
4 G 2 1 3 ... 1 7 5 10
19995 D 2 2 3 ... 2 8 3 7
19996 C 7 10 8 ... 2 9 3 7
19997 T 6 9 6 ... 2 12 2 4
19998 S 2 3 4 ... 1 9 5 8
19999 A 4 9 6 ... 2 7 2 8
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(20000, 16)
shape of y
(20000,)
['A' 'B' 'C' 'D' 'E' 'F' 'G' 'H' 'I' 'J' 'K' 'L' 'M' 'N' 'O' 'P' 'Q' 'R' 'S' 'T' 'U' 'V' 'W' 'X' 'Y' 'Z']
Shape of x_train: (16000, 16)
Shape of x_test: (4000, 16)
Shape of y_train: (16000,)
Shape of y_test: (4000,)
[4 6 6 5 5 7 7 4 4 6 5 8 6 8 4 6]
N
[1 3 1 2 0 7 7 1 8 7 6 8 0 8 3 8]
I
Model: "sequential"
Layer (type) Output Shape Param #
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conda (Python 3.10.9)
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