*Hands-on Activity 5.2: Build and Apply Multilayer Perceptron *

In this assignment, you are task to build a multilayer perceptron model. The following are the requirements:

```
Choose any dataset

Explain the problem you are trying to solve

Create your own model

Evaluate the accuracy of your model
```

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Choose any dataset

print(power_consumption_of_tetouan_city.metadata)

PROBLEM

-In this type of data set i want to solve the possible impact of weather condition in the energy consumption of the people live in Tetouan City using the multilayer perceptron model.

```
pip install ucimlrepo
    Requirement already satisfied: ucimlrepo in /usr/local/lib/python3.10/dist-packages

from ucimlrepo import fetch_ucirepo

# fetch dataset
power_consumption_of_tetouan_city = fetch_ucirepo(id=849)

# data (as pandas dataframes)
X = power_consumption_of_tetouan_city.data.features
y = power_consumption_of_tetouan_city.data.targets

# metadata
```

variable information
print(power_consumption_of_tetouan_city.variables)

{'	uci_id': 849, 'name': 'Power Consu	umption of Teto	uan City',	'repository_url':	' <u>http</u>
	name rol	le type	demographic	\	
0	DateTime Featur	re Date	None		
1	Temperature Featur	re Continuous	None		
2	Humidity Featur	re Continuous	None		
3	Wind Speed Featur	re Continuous	None		
4	general diffuse flows Featur	re Continuous	None		
5	diffuse flows Featur	re Continuous	None		
6	Zone 1 Power Consumption Targe	et Continuous	None		
7	Zone 2 Power Consumption Targe	et Continuous	None		
8	Zone 3 Power Consumption Targe	et Continuous	None		
		description uni	ts missing_v	values	
0	Each t	en minutes No	ne	no	
1	Weather Temperature of Te	etouan city No	ne	no	
2	Weather Humidity of Te	etouan city No	ne	no	
3	Wind speed of Te	etouan city No	ne	no	
4	general dif	fuse flows No	ne	no	
5	dif	fuse flows No	ne	no	
6	power consumption of zone 1 of Te	etouan city No	ne	no	
7	power consumption of zone 2 of Te	etouan city No	ne	no	
8	power consumption of zone 3 of Te	etouan city No	ne	no	

X.tail()

	DateTime	Temperature	Humidity	Wind Speed	general diffuse flows	diffuse flows	
52411	12/30/2017 23:10	7.010	72.4	0.080	0.040	0.096	11.
52412	12/30/2017 23:20	6.947	72.6	0.082	0.051	0.093	
52413	12/30/2017 23:30	6.900	72.8	0.086	0.084	0.074	

y.tail()

	Zone 1 Power Consumption	Zone 2 Power Consumption	Zone 3 Power Consumption	
52411	31160.45627	26857.31820	14780.31212	ıl.
52412	30430.41825	26124.57809	14428.81152	
52413	29590.87452	25277.69254	13806.48259	
52414	28958.17490	24692.23688	13512.60504	
EGAAE	20240 00000	040EE 00467	4224E 40000	

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13343.49020

```
import tensorflow as tf
import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Activation
import matplotlib.pyplot as plt
(X_train, y_train), (X_test, y_test) = tf.keras.datasets.mnist.load_data()
# Cast the records into float values
x_train = X_train.astype('float32')
x_test = X_test.astype('float32')
# normalize image pixel values by dividing
# by 255
gray_scale = 255
x_train /= gray_scale # x_train = x_train/ 255
x_test /= gray_scale
# Understand the structure of the dataset
print("Feature matrix:", x_train.shape)
print("Target matrix:", x_test.shape)
print("Feature matrix:", y_train.shape)
print("Target matrix:", y_test.shape)
     Feature matrix: (60000, 28, 28)
     Target matrix: (10000, 28, 28)
     Feature matrix: (60000,)
     Target matrix: (10000,)
model = Sequential([
# reshape 28 row * 28 column data to 28*28 rows
Flatten(input_shape=(28, 28)),
# dense layer 1
Dense(512, activation='relu'),
# dense layer 2
Dense(256, activation='relu'),
# output layer
Dense(10, activation='softmax'),
])
model.summary()
     Model: "sequential_3"
```

Epoch 9/10

Epoch 10/10

Layer (type)	Output	Shape 	Param # 	·==
flatten_4 (Flatten)	(None,	784)	0	
dense_12 (Dense)	(None,	512)	401920	
dense_13 (Dense)	(None,	256)	131328	
dense_14 (Dense)	(None,	10)	2570	
				
el.compile(optimizer='adam s='sparse_categorical_cros rics=['accuracy'])				
s='sparse_categorical_cros	sentropy',			
s='sparse_categorical_cros rics=['accuracy']) el.fit(x_train, y_train, e ch_size=2000, dation_split=0.2) Epoch 1/10	sentropy', pochs=10,	==] - 5s 146ms/	step - loss:	0.7630 - accuracy:
s='sparse_categorical_cros rics=['accuracy']) el.fit(x_train, y_train, e ch_size=2000, dation_split=0.2) Epoch 1/10 24/24 [====================================	sentropy', pochs=10,	-	•	-
s='sparse_categorical_cros rics=['accuracy']) el.fit(x_train, y_train, e ch_size=2000, dation_split=0.2) Epoch 1/10 24/24 [====================================	sentropy', pochs=10, ===================================	==] - 3s 114ms/	step - loss:	0.2635 - accuracy:
s='sparse_categorical_cros rics=['accuracy']) el.fit(x_train, y_train, ech_size=2000,	sentropy', pochs=10, ==================================	==] - 3s 114ms/ ==] - 3s 109ms/	step - loss: step - loss:	0.2635 - accuracy: 0.1909 - accuracy:
E='sparse_categorical_cros rics=['accuracy']) el.fit(x_train, y_train, e ch_size=2000, dation_split=0.2) Epoch 1/10 24/24 [====================================	sentropy', pochs=10, ==================================	==] - 3s 114ms/ ==] - 3s 109ms/ ==] - 3s 112ms/	step - loss: step - loss: step - loss:	0.2635 - accuracy:0.1909 - accuracy:0.1465 - accuracy:
E='sparse_categorical_croserics=['accuracy']) el.fit(x_train, y_train, enth_size=2000, dation_split=0.2) Epoch 1/10 24/24 [====================================	sentropy', pochs=10, ==================================	==] - 3s 114ms/ ==] - 3s 109ms/ ==] - 3s 112ms/ ==] - 4s 159ms/	step - loss: step - loss: step - loss: step - loss:	0.2635 - accuracy:0.1909 - accuracy:0.1465 - accuracy:0.1156 - accuracy:

<keras.src.callbacks.History at 0x7ece1136dae0>

Evaluate the accuracy of your model

-Achieving 97% accuracy on this model is a very good result, especially considering that the dataset used in the example code is randomly generated it indicates that the MPL is working well and can used to perform prediction and examining the train data.

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