Assignment_5_2

Technological Institute of the Philippines	Quezon City - Computer Engineering
Course Code:	CPE 019
Code Title:	Emerging Technologies in CpE 2
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Assignment 5.2	**Build and Apply Multilayer Perceptron**
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Date Submitted:	June 23, 2024
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Part 1: Try the MLP Notebook using the CIFAR10 Keras Dataset¶

Import libraries¶

In [ ]:

```
import pandas as pd
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Activation
```

Loading Dataset¶

In [ ]:

```
CifarData = cifar10.load_data()
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 [==============================] - 3s 0us/step
```

Convert them into float values¶

In [ ]:

```
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
```

Normalize the data by dividing 255¶

In [ ]:

```
grayscale = 255
x_train /= grayscale
x_test /= grayscale
```

Create the model form¶

In [ ]:

```
CifarModel = Sequential([
        Flatten(input_shape=(32, 32, 3)),
        Dense(512, activation='relu'),
        Dense(256, activation='relu'),
        Dense(10, activation='softmax')
    ])
```

Compile the Model¶

In [ ]:

```
CifarModel.compile(optimizer='adam',
                   loss='sparse_categorical_crossentropy',
                   metrics=['accuracy'])
```

Fit the Model¶

In [ ]:

```
CifarModel.fit(x_train, y_train, epochs=10,
               batch_size = 2000,
               validation_split = 0.2)
```

```
Epoch 1/10
20/20 [==============================] - 8s 308ms/step - loss: 2.5125 - accuracy: 0.1694 - val_loss: 2.0674 - val_accuracy: 0.2654
Epoch 2/10
20/20 [==============================] - 7s 354ms/step - loss: 1.9926 - accuracy: 0.2914 - val_loss: 1.9521 - val_accuracy: 0.3092
Epoch 3/10
20/20 [==============================] - 6s 326ms/step - loss: 1.8915 - accuracy: 0.3355 - val_loss: 1.8929 - val_accuracy: 0.3300
Epoch 4/10
```

```
20/20 [==============================] - 8s 418ms/step - loss: 1.8488 -
accuracy: 0.3458 - val_loss: 1.8578 - val_accuracy: 0.3306
Epoch 5/10
20/20 [==============================] - 6s 281ms/step - loss: 1.7978 -
accuracy: 0.3643 - val_loss: 1.8004 - val_accuracy: 0.3613
Epoch 6/10
20/20 [==============================] - 7s 370ms/step - loss: 1.7480 -
accuracy: 0.3839 - val_loss: 1.7776 - val_accuracy: 0.3746
Epoch 7/10
20/20 [==============================] - 6s 280ms/step - loss: 1.7237 -
accuracy: 0.3925 - val_loss: 1.7436 - val_accuracy: 0.3881
Epoch 8/10
20/20 [==============================] - 7s 342ms/step - loss: 1.6921 -
accuracy: 0.4015 - val_loss: 1.7071 - val_accuracy: 0.4058
Epoch 9/10
20/20 [==============================] - 6s 292ms/step - loss: 1.6629 -
accuracy: 0.4158 - val_loss: 1.6973 - val_accuracy: 0.4021
Epoch 10/10
20/20 [==============================] - 6s 305ms/step - loss: 1.6395 -
accuracy: 0.4227 - val_loss: 1.6833 - val_accuracy: 0.4030
```

Out[ ]:

```
<keras.src.callbacks.History at 0x7f1f2a0d8a60>
```

Find the accuracy of the Model¶

In [ ]:

```
CifarResults = CifarModel.evaluate(x_test, y_test, verbose = 1)
print('test loss, test acc:', CifarResults)
```

```
313/313 [==============================] - 2s 6ms/step - loss: 1.6583 -
accuracy: 0.4091
test loss, test acc: [1.6583114862442017, 0.4090999960899353]
```

Part 2:¶

Choose any dataset¶

Importing Libraries¶

In [28]:

```
import pandas as pd
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Flatten
```

```
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Activation
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
```

Loading Dataset¶

Resource: https://archive.ics.uci.edu/dataset/19/car+evaluation

In [29]:

```
ColumnNames = ['buying', 'maint', 'doors', 'persons', 'lug_boot', 'safety',
'class']
CarData = pd.read_csv('/content/drive/MyDrive/CPE 019 (Retake)/Assignment
5.2/car.data', header=None)
CarData.columns = ColumnNames
CarData.to_csv('/content/drive/MyDrive/CPE 019 (Retake)/Assignment
5.2/data_with_header.csv', index=False)
CarData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1728 entries, 0 to 1727
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   buying    1728 non-null   object
 1   maint     1728 non-null   object
 2   doors     1728 non-null   object
 3   persons   1728 non-null   object
 4   lug_boot  1728 non-null   object
 5   safety    1728 non-null   object
 6   class     1728 non-null   object
dtypes: object(7)
memory usage: 94.6+ KB
```

In [30]:

```
CarData
```

Out[30]:

	buying	maint	doors	persons	lug_boot	safety	class
0	vhigh	vhigh	2	2	small	low	unacc
1	vhigh	vhigh	2	2	small	med	unacc
2	vhigh	vhigh	2	2	small	high	unacc
3	vhigh	vhigh	2	2	med	low	unacc
4	vhigh	vhigh	2	2	med	med	unacc
...	...	...	...	...	...	...	...

1723	low	low	5more	more	med	med	good
1724	low	low	5more	more	med	high	vgood
1725	low	low	5more	more	big	low	unacc
1726	low	low	5more	more	big	med	good
1727	low	low	5more	more	big	high	vgood

1728 rows × 7 columns

Explain the problem you are trying to solve¶

- The problem that is trying to solve is to determine the condition of the vehicles, wether it has an accident history or the remaining lifespan, also categorizing cars into various classes based on features. The goal is to develop a system that determining the Car evaluation with such giving description.

Create your own model¶

In [31]:

```
CarData.describe()
```

Out[31]:

	buying	maint	doors	persons	lug_boot	safety	class
count	1728	1728	1728	1728	1728	1728	1728
unique	4	4	4	3	3	3	4
top	vhigh	vhigh	2	2	small	low	unacc
freq	432	432	432	576	576	576	1210

Convert all rows into int values¶

In [32]:

```
LE = LabelEncoder()
for col in CarData.columns:
    if CarData[col].dtype == 'object':
      CarData[col] = LE.fit_transform(CarData[col])
    else:
      pass
CarData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1728 entries, 0 to 1727
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   buying    1728 non-null   int64
 1   maint     1728 non-null   int64
```

```
 2   doors     1728 non-null   int64
 3   persons   1728 non-null   int64
 4   lug_boot  1728 non-null   int64
 5   safety    1728 non-null   int64
 6   class     1728 non-null   int64
dtypes: int64(7)
memory usage: 94.6 KB
```

In [33]:

```
CarData
```

Out[33]:

	buying	maint	doors	persons	lug_boot	safety	class
0	3	3	0	0	2	1	2
1	3	3	0	0	2	2	2
2	3	3	0	0	2	0	2
3	3	3	0	0	1	1	2
4	3	3	0	0	1	2	2
...	...	...	...	...	...	...	...
1723	1	1	3	2	1	2	1
1724	1	1	3	2	1	0	3
1725	1	1	3	2	0	1	2
1726	1	1	3	2	0	2	1
1727	1	1	3	2	0	0	3

1728 rows × 7 columns

In [34]:

```
CarData.describe()
```

Out[34]:

	buying	maint	doors	persons	lug_boot	safety	class
count	1728.000000	1728.000000	1728.000000	1728.000000	1728.000000	1728.000000	1728.000000
mean	1.500000	1.500000	1.500000	1.000000	1.000000	1.000000	1.553241
std	1.118358	1.118358	1.118358	0.816733	0.816733	0.816733	0.875948
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

25%	0.750000	0.750000	0.750000	0.000000	0.000000	0.000000	1.000000
50%	1.500000	1.500000	1.500000	1.000000	1.000000	1.000000	2.000000
75%	2.250000	2.250000	2.250000	2.000000	2.000000	2.000000	2.000000
max	3.000000	3.000000	3.000000	2.000000	2.000000	2.000000	3.000000

Splitting X and y values¶

In [35]:

```
X = CarData.iloc[:, :-1].values
y = CarData.iloc[:, -1].values
```

In [36]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
random_state=123)
```

Standardizing the X_train and X_test variables¶

In [38]:

```
SS = StandardScaler()
X_train = SS.fit_transform(X_train)
X_test = SS.fit_transform(X_test)
```

Displaying the shape of X and y split¶

In [39]:

```
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: (1296, 6)
Target matrix: (432, 6)
Feature matrix: (1296,)
Target matrix: (432,)
```

Creating Model¶

In [71]:

```
CarDataModel = Sequential([
        Flatten(input_shape=(6,)),
        Dense(512, activation='relu'),
        Dense(256, activation='relu'),
```

```
        Dense(5, activation='softmax')
])
```

Summary the Model¶

In [72]:

```
CarDataModel.summary()
```

```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 flatten_8 (Flatten)         (None, 6)                 0         
                                                                 
 dense_24 (Dense)            (None, 512)               3584      
                                                                 
 dense_25 (Dense)            (None, 256)               131328    
                                                                 
 dense_26 (Dense)            (None, 5)                 1285      
                                                                 
=================================================================
Total params: 136197 (532.02 KB)
Trainable params: 136197 (532.02 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Compile the Model¶

In [73]:

```
CarDataModel.compile(optimizer='adam',
                     loss='sparse_categorical_crossentropy',
                     metrics=['accuracy'])
```

Fit the Model¶

In [83]:

```
history = CarDataModel.fit(X_train, y_train, epochs=20,
                 batch_size = 2000,
                 validation_split = 0.2)
```

```
Epoch 1/20
1/1 [==============================] - 0s 118ms/step - loss: 0.4258 - accuracy: 0.8427 - val_loss: 0.4092 - val_accuracy: 0.8077
Epoch 2/20
1/1 [==============================] - 0s 77ms/step - loss: 0.4182 - accuracy: 0.8456 - val_loss: 0.4023 - val_accuracy: 0.8154
Epoch 3/20
1/1 [==============================] - 0s 59ms/step - loss: 0.4107 - accuracy: 0.8475 - val_loss: 0.3954 - val_accuracy: 0.8192
```

```
Epoch 4/20
1/1 [==============================] - 0s 74ms/step - loss: 0.4033 -
accuracy: 0.8494 - val_loss: 0.3884 - val_accuracy: 0.8308
Epoch 5/20
1/1 [==============================] - 0s 78ms/step - loss: 0.3959 -
accuracy: 0.8533 - val_loss: 0.3814 - val_accuracy: 0.8423
Epoch 6/20
1/1 [==============================] - 0s 76ms/step - loss: 0.3885 -
accuracy: 0.8571 - val_loss: 0.3743 - val_accuracy: 0.8538
Epoch 7/20
1/1 [==============================] - 0s 86ms/step - loss: 0.3812 -
accuracy: 0.8591 - val_loss: 0.3673 - val_accuracy: 0.8538
Epoch 8/20
1/1 [==============================] - 0s 78ms/step - loss: 0.3740 -
accuracy: 0.8600 - val_loss: 0.3605 - val_accuracy: 0.8654
Epoch 9/20
1/1 [==============================] - 0s 73ms/step - loss: 0.3671 -
accuracy: 0.8697 - val_loss: 0.3540 - val_accuracy: 0.8769
Epoch 10/20
1/1 [==============================] - 0s 76ms/step - loss: 0.3603 -
accuracy: 0.8755 - val_loss: 0.3478 - val_accuracy: 0.8808
Epoch 11/20
1/1 [==============================] - 0s 83ms/step - loss: 0.3537 -
accuracy: 0.8832 - val_loss: 0.3419 - val_accuracy: 0.8846
Epoch 12/20
1/1 [==============================] - 0s 76ms/step - loss: 0.3471 -
accuracy: 0.8861 - val_loss: 0.3364 - val_accuracy: 0.8846
Epoch 13/20
1/1 [==============================] - 0s 61ms/step - loss: 0.3407 -
accuracy: 0.8861 - val_loss: 0.3311 - val_accuracy: 0.8846
Epoch 14/20
1/1 [==============================] - 0s 70ms/step - loss: 0.3344 -
accuracy: 0.8861 - val_loss: 0.3260 - val_accuracy: 0.8885
Epoch 15/20
1/1 [==============================] - 0s 93ms/step - loss: 0.3283 -
accuracy: 0.8861 - val_loss: 0.3210 - val_accuracy: 0.8885
Epoch 16/20
1/1 [==============================] - 0s 77ms/step - loss: 0.3223 -
accuracy: 0.8871 - val_loss: 0.3159 - val_accuracy: 0.9000
Epoch 17/20
1/1 [==============================] - 0s 81ms/step - loss: 0.3165 -
accuracy: 0.8890 - val_loss: 0.3110 - val_accuracy: 0.8962
Epoch 18/20
1/1 [==============================] - 0s 69ms/step - loss: 0.3108 -
accuracy: 0.8948 - val_loss: 0.3061 - val_accuracy: 0.8962
Epoch 19/20
1/1 [==============================] - 0s 64ms/step - loss: 0.3052 -
accuracy: 0.8967 - val_loss: 0.3014 - val_accuracy: 0.9000
Epoch 20/20
```

```
1/1 [==============================] - 0s 63ms/step - loss: 0.2998 - accuracy: 0.8986 - val_loss: 0.2969 - val_accuracy: 0.9000
```

In [81]:

```
history.history.keys()
```

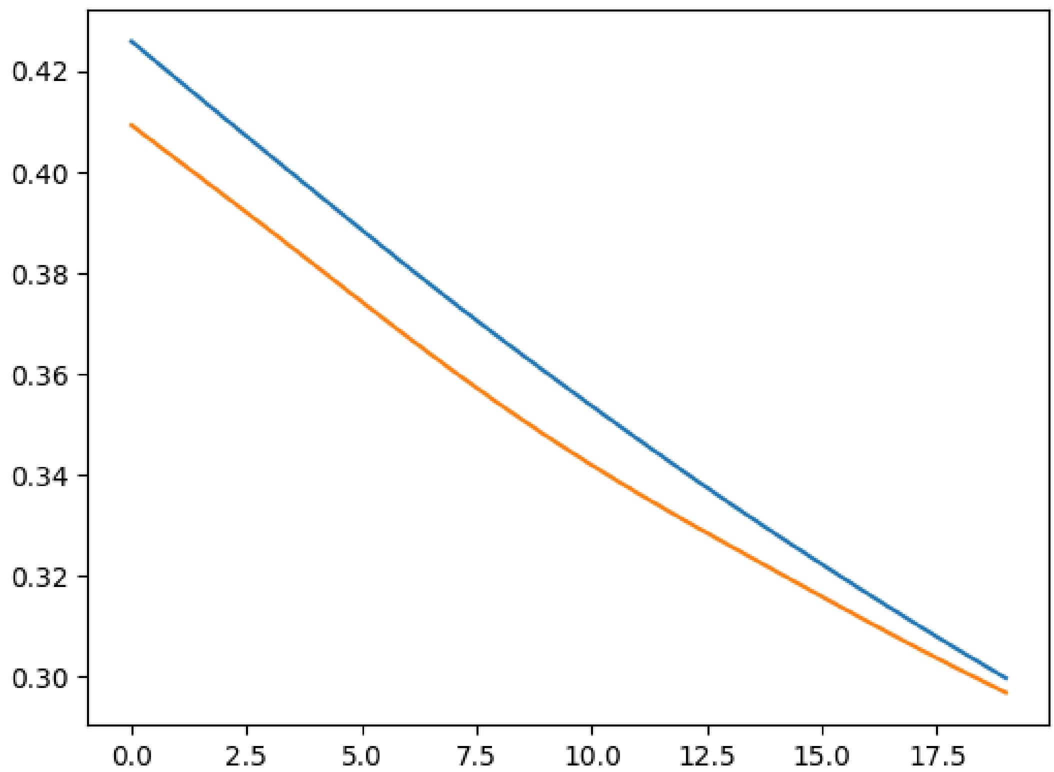
Out[81]:

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

Plot the Result of the Model¶

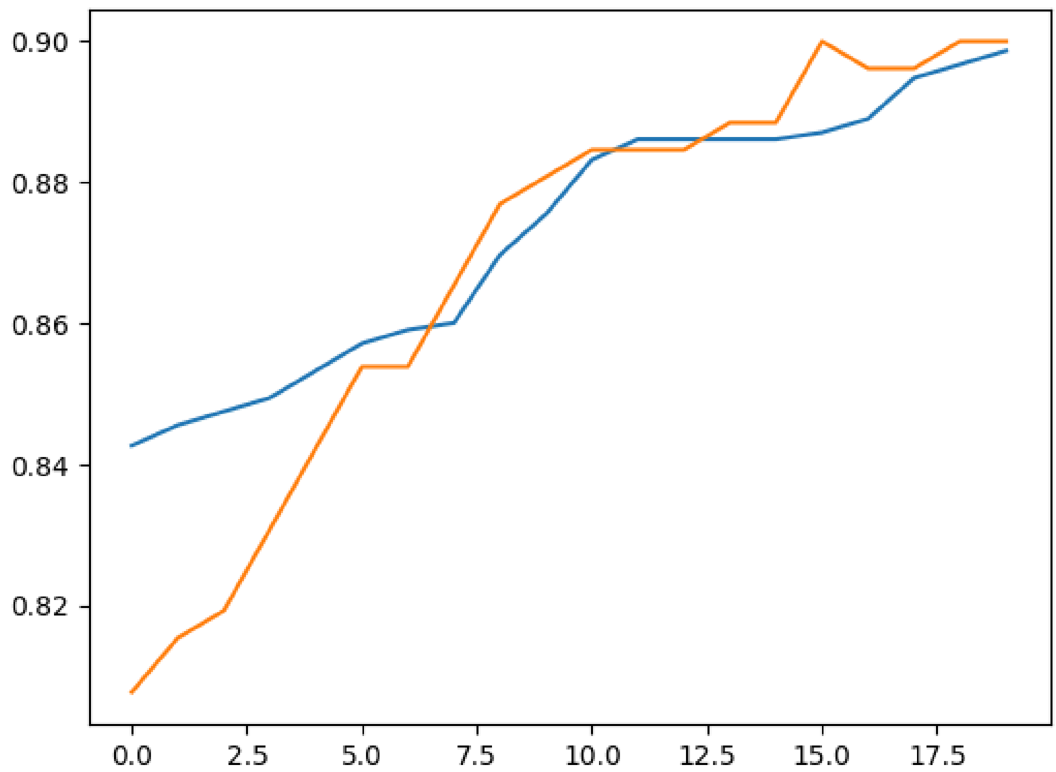
In [85]:

```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.show()
```



In [86]:

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.show()
```



Evaluate the accuracy of your model¶

In [90]:

```
CarDataResults = CarDataModel.evaluate(X_test, y_test, verbose = 1)
print('test loss, test acc:', CarDataResults)
```

```
14/14 [==============================] - 0s 5ms/step - loss: 0.3260 -
accuracy: 0.8819
test loss, test acc: [0.32595106959342957, 0.8819444179534912]
```

- The Accuracy that we have got in the model is 88.19% with a loss of 32.4%

In [ ]:

```
!jupyter nbconvert --to html /content/Assignment_5_2.ipynb
```

```
[NbConvertApp] Converting notebook /content/Assignment_5_2.ipynb to html
[NbConvertApp] Writing 595952 bytes to /content/Assignment_5_2.html
```

In [ ]:

```
!pandoc Assignment_5_2.html -s -o Assignment_5_2.docx
```