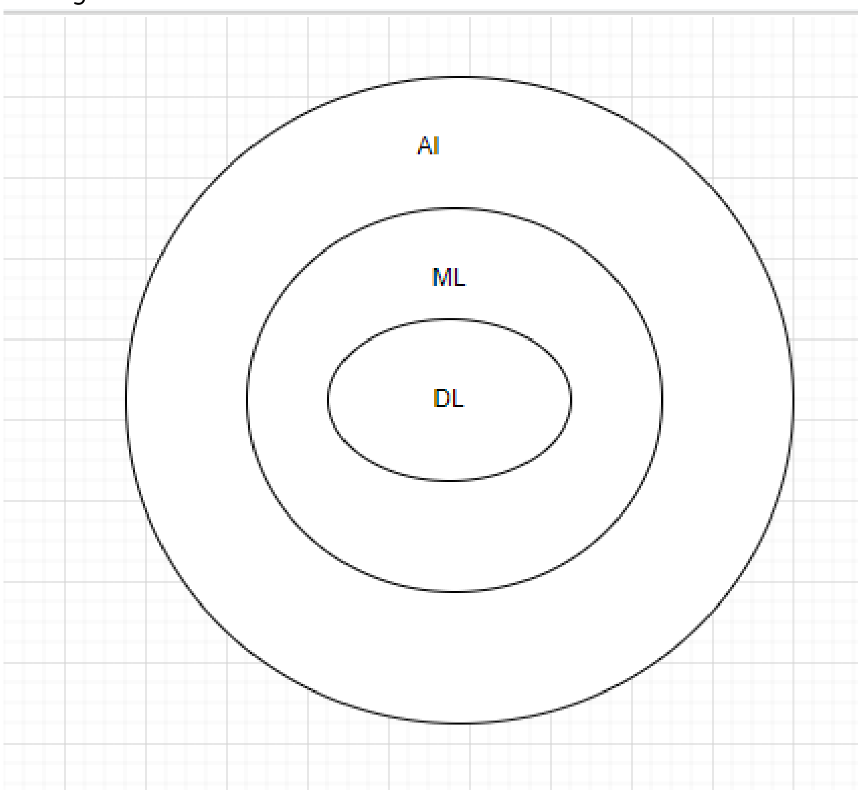
```
#Dataset : https://raw.githubusercontent.com/shakil1819/CSE442-Machine-Learning-Sessional/main/Week%208%20-%20CNN%20ANN/car_purchasing.csv
```

Notes

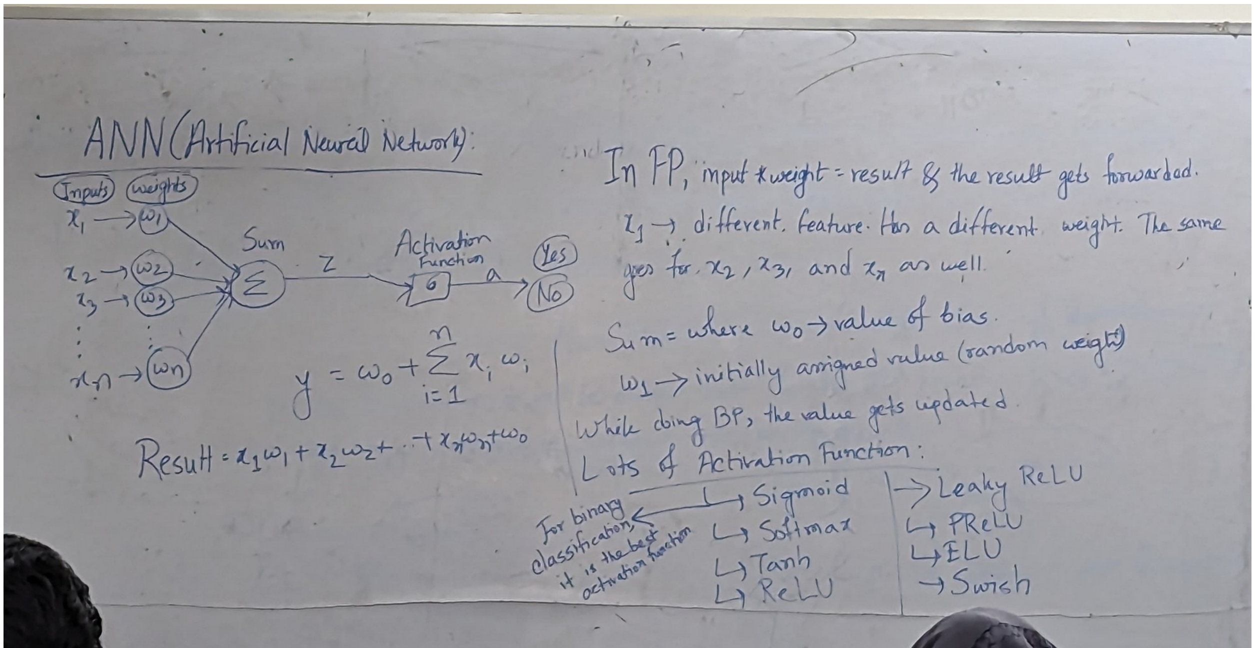
- AI is the simulation of human intelligence processes by reaction,expecially computer systems
- ML is the study that uses statistical methods to enable machines to improve with experience
- DL is a subset of ML, which is a subset of AI DL uses Neural Networks(Similar to neurons of brain) to imitate functionalities just like a human brain
- DL+Linguistics+NLP+CS = ChatGPT
- 

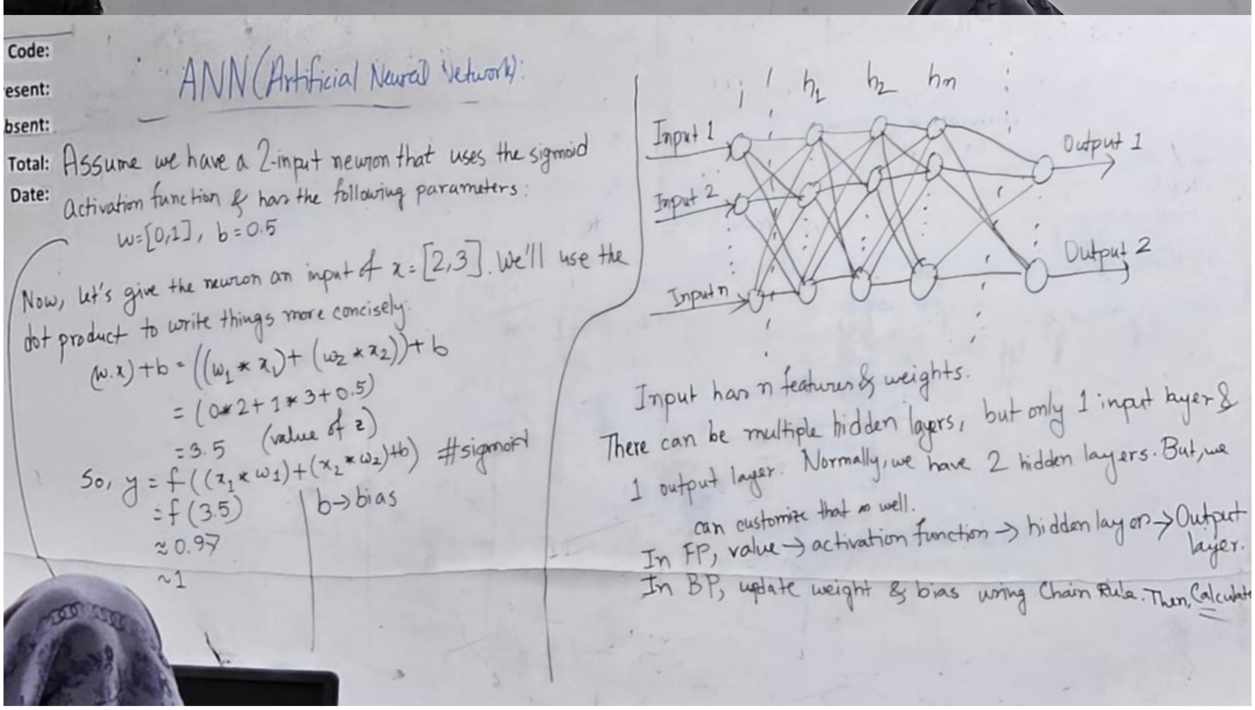
Neuron Comparison

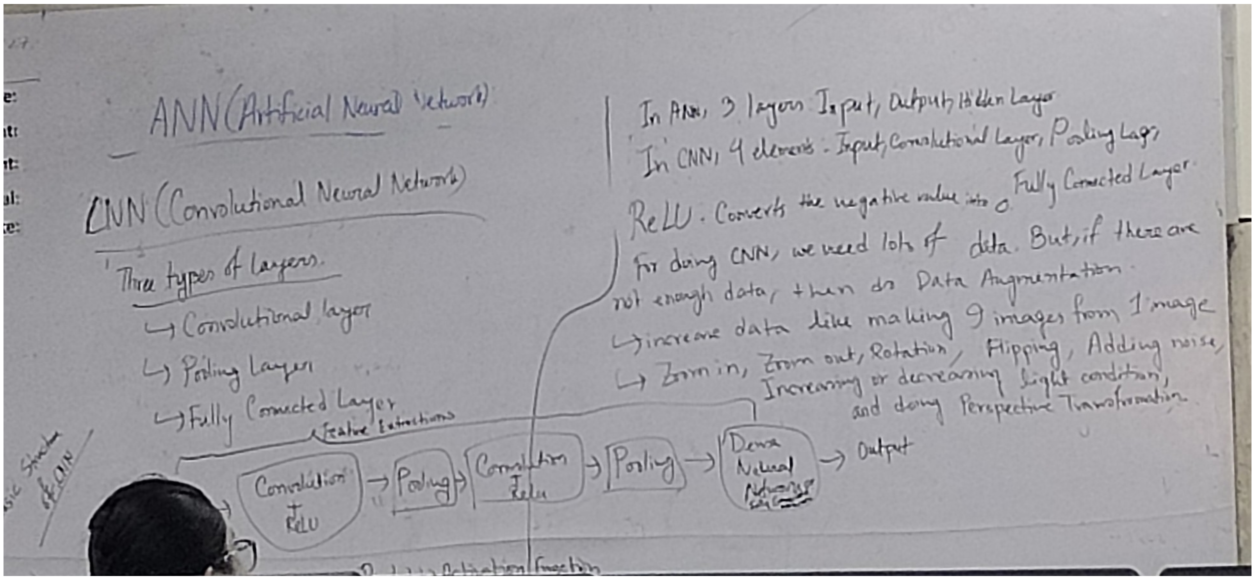
- Dendrite =Input
- Soma = cell body (Calculation)
- Axon = Receives Results

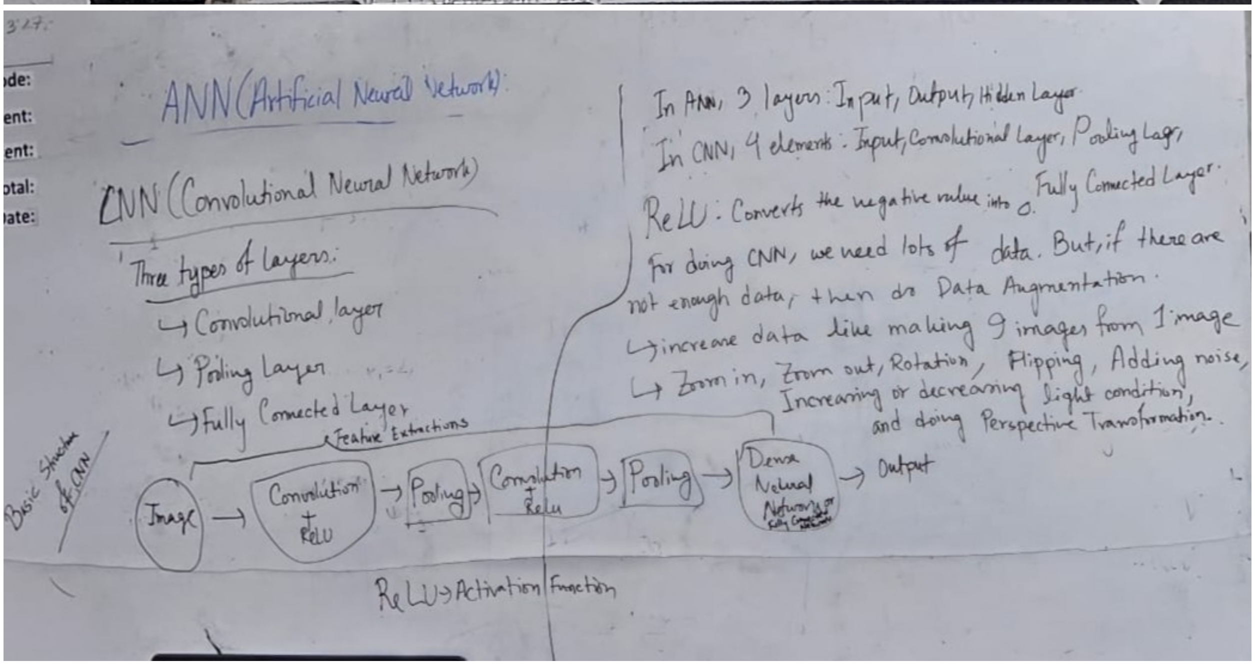
- Axon Terminals = Info will be received by another neuron .For the 1st neuron It will be Output but for 2nd one it will be input. Like this way a network is created from lots of neuron.

ANN (Artificial neural Network)









Library

```
import pandas as pd
import numpy as np
import seaborn as sb
import matplotlib.pyplot as plt
from warnings import filterwarnings
```

Read data

```
path = "https://raw.githubusercontent.com/shakil1819/CSE442-Machine-Learning-Sessional/main/Week%208%20-%20CNN%20ANN/car_purchasing.csv"
```

```python
df = pd.read_csv(path,encoding='ISO-8859-1')
df.head()
```

```
      customer name                                     customer e-mail  \
0     Martina Avila  cubilia.Curae.Phasellus@quisaccumsanconvallis.edu

1     Harlan Barnes                                eu.dolor@diam.co.uk

2  Naomi Rodriquez  vulputate.mauris.sagittis@ametconsectetueradip...

3  Jade Cunningham                            malesuada@dignissim.com

4      Cedric Leach     felis.ullamcorper.viverra@egetmollislectus.net


        country  gender        age  annual Salary  credit card debt  \
0      Bulgaria       0  41.851720    62812.09301      11609.380910
1        Belize       0  40.870623    66646.89292       9572.957136
2       Algeria       1  43.152897    53798.55112      11160.355060
3  Cook Islands       1  58.271369    79370.03798      14426.164850
4        Brazil       1  57.313749    59729.15130       5358.712177

     net worth  car purchase amount
0  238961.2505          35321.45877
1  530973.9078          45115.52566
2  638467.1773          42925.70921
3  548599.0524          67422.36313
4  560304.0671          55915.46248
```

```python
df.describe()
```

```
           gender         age  annual Salary  credit card debt  \
count  500.000000  500.000000     500.000000        500.000000
mean     0.506000   46.241674   62127.239608       9607.645049
std      0.500465    7.978862   11703.378228       3489.187973
min      0.000000   20.000000   20000.000000        100.000000
25%      0.000000   40.949969   54391.977195       7397.515792
50%      1.000000   46.049901   62915.497035       9655.035568
75%      1.000000   51.612263   70117.862005      11798.867487
max      1.000000   70.000000  100000.000000      20000.000000

            net worth  car purchase amount
count      500.000000           500.000000
mean    431475.713625         44209.799218
std     173536.756340         10773.178744
min      20000.000000          9000.000000
25%     299824.195900         37629.896040
50%     426750.120650         43997.783390
75%     557324.478725         51254.709517
max    1000000.000000         80000.000000
```

```
df.info()
#we can see from the output that there is no null value
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 9 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   customer name        500 non-null    object 
 1   customer e-mail      500 non-null    object 
 2   country              500 non-null    object 
 3   gender               500 non-null    int64  
 4   age                  500 non-null    float64
 5   annual Salary        500 non-null    float64
 6   credit card debt     500 non-null    float64
 7   net worth            500 non-null    float64
 8   car purchase amount  500 non-null    float64
dtypes: float64(5), int64(1), object(3)
memory usage: 35.3+ KB
```

Test Train Split

```
X = df.drop(['customer name','customer e-mail','country','car purchase 
amount','gender'],axis=1)
y = df[['car purchase amount']]
```

```
from sklearn.preprocessing import MinMaxScaler
MMS = MinMaxScaler()
X_scaled = MMS.fit_transform(X)
Y_scaled = MMS.fit_transform(y.values.reshape(-1,1))
X_scaled.shape
```

```
(500, 4)
```

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = 
train_test_split(X_scaled,Y_scaled,test_size=0.25,random_state=101)
X_train.shape
```

```
(375, 4)
```

```
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras import callbacks
model = keras.Sequential([
    layers.Dense(50, activation='relu', input_shape=[4]),
    layers.Dense(25, activation='relu'),
    layers.Dropout(0.3),
    layers.Dense(1,activation='linear')
])
```

```
model.compile(
    optimizer='adam',
    loss='mean_squared_error',
)

history = model.fit(X_train, y_train,
batch_size=16,validation_split=0.2,epochs=50)
```

```
Epoch 1/50
19/19 [==============================] - 1s 12ms/step - loss: 0.0565 -
val_loss: 0.0093
Epoch 2/50
19/19 [==============================] - 0s 4ms/step - loss: 0.0262 -
val_loss: 0.0075
Epoch 3/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0195 -
val_loss: 0.0065
Epoch 4/50
19/19 [==============================] - 0s 4ms/step - loss: 0.0163 -
val_loss: 0.0060
Epoch 5/50
19/19 [==============================] - 0s 4ms/step - loss: 0.0156 -
val_loss: 0.0053
Epoch 6/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0170 -
val_loss: 0.0040
Epoch 7/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0131 -
val_loss: 0.0049
Epoch 8/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0128 -
val_loss: 0.0033
Epoch 9/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0121 -
val_loss: 0.0040
Epoch 10/50
19/19 [==============================] - 0s 4ms/step - loss: 0.0111 -
val_loss: 0.0025
Epoch 11/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0112 -
val_loss: 0.0028
Epoch 12/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0097 -
val_loss: 0.0021
Epoch 13/50
19/19 [==============================] - 0s 4ms/step - loss: 0.0104 -
val_loss: 0.0025
Epoch 14/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0102 -
val_loss: 0.0030
```

```
Epoch 15/50
19/19 [==============================] - 0s 4ms/step - loss: 0.0090 -
val_loss: 0.0014
Epoch 16/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0105 -
val_loss: 0.0016
Epoch 17/50
19/19 [==============================] - 0s 4ms/step - loss: 0.0079 -
val_loss: 0.0020
Epoch 18/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0085 -
val_loss: 0.0048
Epoch 19/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0093 -
val_loss: 0.0021
Epoch 20/50
19/19 [==============================] - 0s 2ms/step - loss: 0.0076 -
val_loss: 8.6871e-04
Epoch 21/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0071 -
val_loss: 0.0010
Epoch 22/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0076 -
val_loss: 0.0013
Epoch 23/50
19/19 [==============================] - 0s 4ms/step - loss: 0.0091 -
val_loss: 0.0010
Epoch 24/50
19/19 [==============================] - 0s 2ms/step - loss: 0.0063 -
val_loss: 6.4912e-04
Epoch 25/50
19/19 [==============================] - 0s 2ms/step - loss: 0.0072 -
val_loss: 7.6781e-04
Epoch 26/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0070 -
val_loss: 0.0018
Epoch 27/50
19/19 [==============================] - 0s 2ms/step - loss: 0.0063 -
val_loss: 5.4303e-04
Epoch 28/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0073 -
val_loss: 7.6640e-04
Epoch 29/50
19/19 [==============================] - 0s 2ms/step - loss: 0.0065 -
val_loss: 0.0012
Epoch 30/50
19/19 [==============================] - 0s 2ms/step - loss: 0.0063 -
val_loss: 0.0018
Epoch 31/50
```

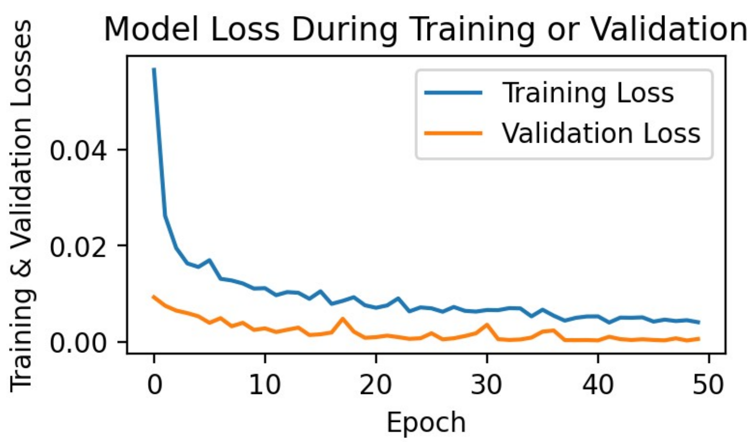
```
19/19 [==============================] - 0s 2ms/step - loss: 0.0066 -
val_loss: 0.0036
Epoch 32/50
19/19 [==============================] - 0s 2ms/step - loss: 0.0066 -
val_loss: 5.8585e-04
Epoch 33/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0070 -
val_loss: 4.1645e-04
Epoch 34/50
19/19 [==============================] - 0s 2ms/step - loss: 0.0070 -
val_loss: 5.1434e-04
Epoch 35/50
19/19 [==============================] - 0s 2ms/step - loss: 0.0053 -
val_loss: 9.1231e-04
Epoch 36/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0067 -
val_loss: 0.0021
Epoch 37/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0055 -
val_loss: 0.0024
Epoch 38/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0044 -
val_loss: 3.9007e-04
Epoch 39/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0050 -
val_loss: 3.7804e-04
Epoch 40/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0053 -
val_loss: 3.9449e-04
Epoch 41/50
19/19 [==============================] - 0s 2ms/step - loss: 0.0053 -
val_loss: 3.2463e-04
Epoch 42/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0040 -
val_loss: 0.0011
Epoch 43/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0051 -
val_loss: 5.8737e-04
Epoch 44/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0050 -
val_loss: 4.0895e-04
Epoch 45/50
19/19 [==============================] - 0s 2ms/step - loss: 0.0051 -
val_loss: 5.5512e-04
Epoch 46/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0042 -
val_loss: 4.1330e-04
Epoch 47/50
19/19 [==============================] - 0s 4ms/step - loss: 0.0046 -
```

```
val_loss: 3.3257e-04
Epoch 48/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0043 -
val_loss: 7.5633e-04
Epoch 49/50
19/19 [==============================] - 0s 2ms/step - loss: 0.0045 -
val_loss: 3.0635e-04
Epoch 50/50
19/19 [==============================] - 0s 3ms/step - loss: 0.0041 -
val_loss: 6.2181e-04
```

```
plt.figure(figsize=(4,2),dpi=200)
plt.plot(history.history["loss"])
plt.plot(history.history["val_loss"])

plt.title('Model Loss During Training or Validation')
plt.ylabel('Training & Validation Losses')
plt.xlabel('Epoch')
plt.legend(['Training Loss', 'Validation Loss'])
```

```
<matplotlib.legend.Legend at 0x7a706531a110>
```




```
loss = model.evaluate(X_test, y_test)
print(loss)
```

```
4/4 [==============================] - 0s 2ms/step - loss: 4.0405e-04
0.00040404516039416194
```

```
X_random_sample = np.array([[ 55, 65000, 11600, 562341]])
y_predict = model.predict(X_random_sample)
print('Predicted Purchase Amount is =', y_predict[:,0])
```

```
1/1 [==============================] - 0s 62ms/step
Predicted Purchase Amount is = [198267.56]
```