ANN_Regression_Car_Sales_Price_Prediction

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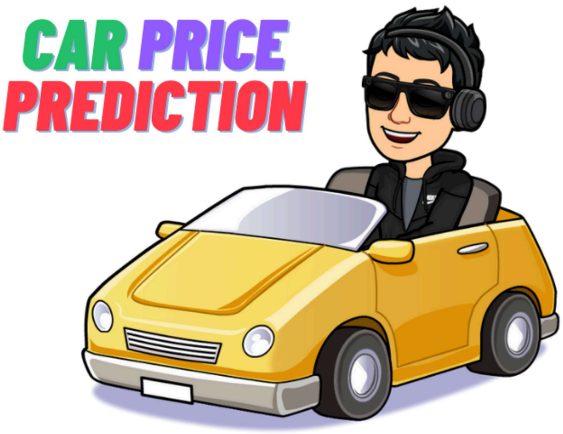


Objective:

The objective of this assignment is to build and train an Artificial Neural Network (ANN) model using the Car Sales dataset.

Skills:

- data preprocessing,
- exploratory data analysis
- model architecture development,
- training, and
- evaluation to predict car sales based on various features.

Main Context:-

As a vehicle salesperson, its desired to create a model that can estimate the overall amount that consumers would spend given the following characteristics:

- customer name,
- customer email,
- country,
- gender,
- age,
- annual salary,
- credit card debt, and
- net worth

The model should anticipate the following (Problem Statement):

Amount Paid for a Car

Task type:

Regression

Tasks

Data Pre-Processing

Loading the dataset and importing the libraries

In [1]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.layers import Dense, Dropout
from keras.models import Sequential

from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
```

Note:

While reading csv you will face an error UnicodeDecodeError Just do the following step while reading csv file:-

```python
data = pd.read_csv("/kaggle/input/ann-car-sales-price-prediction/car_purchasing.csv",encoding='ISO-8859-1')
```

In [2]:

```
df= pd.read_csv('car_purchasing.csv', encoding='ISO-8859-1')
df.tail()
```

Out[2]:

	customer name	customer e-mail	country	gender	age	annual Salary	credit card debt	net worth	car purchase amount
495	Walter	ligula@Cumsociis.ca	Nepal	0	41.462515	71942.40291	6995.902524	541670.1016	48901.44342
496	Vanna	Cum.sociis.natoque@Sedmolestie.edu	Zimbabwe	1	37.642000	56039.49793	12301.456790	360419.0988	31491.41457
497	Pearl	penatibus.et@massanonante.com	Philippines	1	53.943497	68888.77805	10611.606860	764531.3203	64147.28888
498	Nell	Quisque.varius@arcuVivamussit.net	Botswana	1	59.160509	49811.99062	14013.034510	337826.6382	45442.15353
499	Marla	Camaron.marla@hotmail.com	marlal	1	46.731152	61370.67766	9391.341628	462946.4924	45107.22566

Exploratory data analysis

In [3]:

```
# checking the info
df.info()
```

```
<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
```

- Observations:

    1. Dataset size is 500 rows x 9 columns
    2. NO null/ missing values in the dataset

.

In [4]:

```
# checking describe on the dataset
df.describe(include= 'all')
```

Out[4]:

	customer name	customer e-mail	country	gender	age	annual Salary	credit card debt	net worth	car purchase amount
count	500	500	500	500.000000	500.000000	500.000000	500.000000	500.000000	500.000000
unique	498	500	211	NaN	NaN	NaN	NaN	NaN	NaN
top	Seth	cubilia.Curae.Phasellus@quisaccumsanconvallis.edu	Israel	NaN	NaN	NaN	NaN	NaN	NaN
freq	2	1	6	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	NaN	NaN	0.506000	46.241674	62127.239608	9607.645049	431475.713625	44209.799218
std	NaN	NaN	NaN	0.500465	7.978862	11703.378228	3489.187973	173536.756340	10773.178744
min	NaN	NaN	NaN	0.000000	20.000000	20000.000000	100.000000	20000.000000	9000.000000
25%	NaN	NaN	NaN	0.000000	40.949969	54391.977195	7397.515792	299824.195900	37629.896040
50%	NaN	NaN	NaN	1.000000	46.049901	62915.497035	9655.035568	426750.120650	43997.783390
75%	NaN	NaN	NaN	1.000000	51.612263	70117.862005	11798.867487	557324.478725	51254.709517
max	NaN	NaN	NaN	1.000000	70.000000	100000.000000	20000.000000	1000000.000000	80000.000000

Observations:

1. Dataset has customer base of 211 different countries
2. Gender column has int datatype and represents 0: Male and 1: Female
3. Age column varies from 20 to 70 yead, with avg age of 46.2 years
4. Avg Annual Salary is 62,127, avg debt is 9,607, avg net worth is 431,475 and avg car purchase amount is 44,209.
5. Assuming all values are in USD ($)

In [5]:

```
# count of male & feamle
df.gender.value_counts()
```

Out[5]:

```
gender
1    253
0    247
Name: count, dtype: int64
```

Male: 247, Female: 253

In [6]:

```
# Top 10 countires represented in the dataset (by respective customer count)
df.country.value_counts().head(10)
```

Out[6]:

```
country
Israel              6
Mauritania          6
Bolivia             6
Greenland           5
Saint Barthélemy    5
Guinea              5
Iraq                5
Samoa               5
Liechtenstein       5
Bhutan              5
Name: count, dtype: int64
```

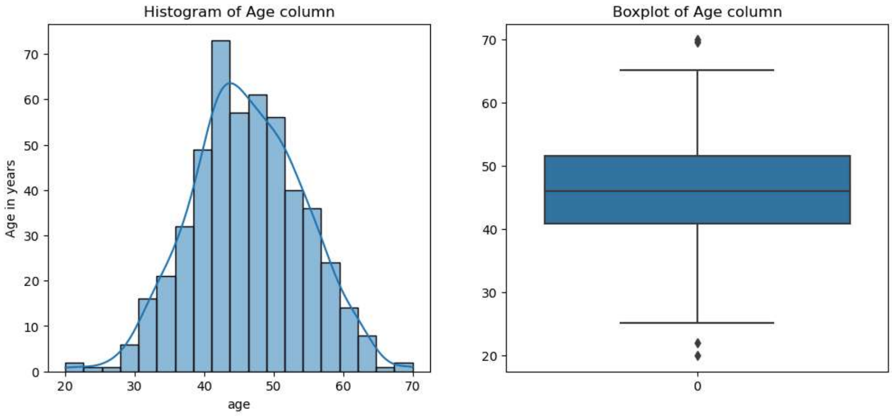
In [7]:

```
# customer name and customer e-mail are unique features, and can be dropped
# country and gender can also be dropped
df.drop(columns = ['customer name','customer e-mail','country','gender'], inplace= True)
```

In [8]:

```python
# age
plt.figure(figsize = (12,5))
plt.subplot(1,2,1)
sns.histplot(df.age, kde = True)
plt.title('Histogram of Age column')
plt.ylabel('Age in years')

plt.subplot(1,2,2)
sns.boxplot(df.age)
plt.title('Boxplot of Age column')
plt.show()
```



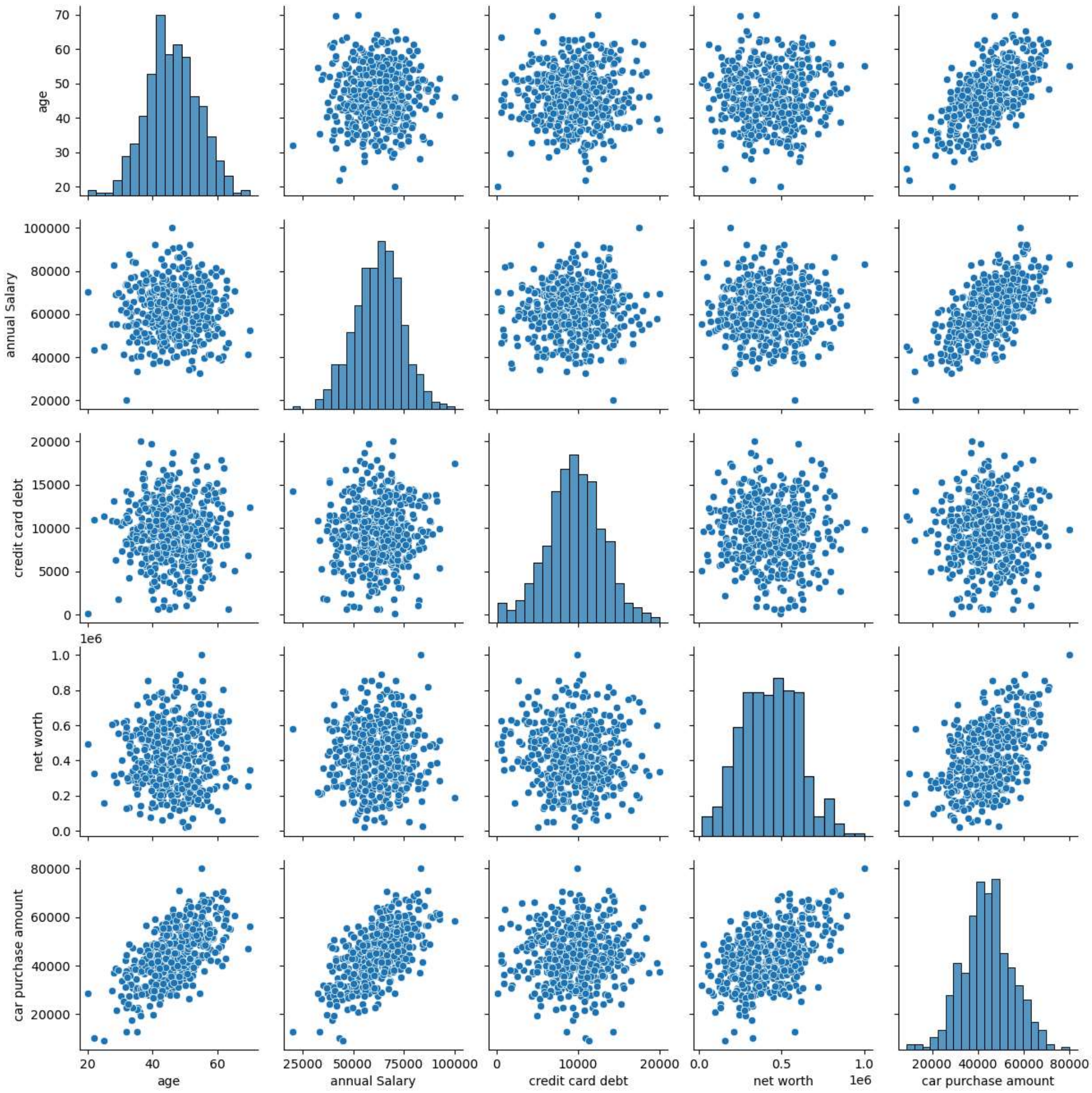
Age column is approximately normally distributed and has outliers at both the ends

In [9]:

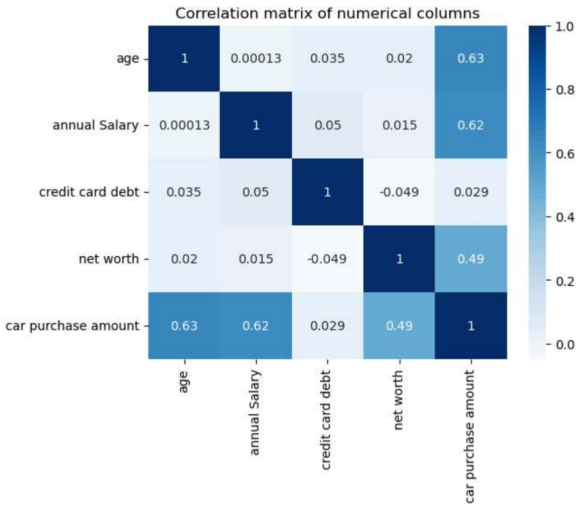
```python
# Pairplot for Numerical columns

sns.pairplot(df)
plt.show()
```

```
E:\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



In [10]:
```
#correation matrix
corr= df.corr(numeric_only = True)
sns.heatmap(corr, annot = True, cmap="Blues")
plt.title('Correlation matrix of numerical columns')
plt.show()
```



Observations:

1. As per correlatin matrix, target col = Car purchase amount, has slightly positive relationship with Age, Annual Salary and net-worth

Encoding: LabelEncoder

Observation:

Since, all columns are numerical, there is no need for Encoding

In [11]:
```
df.head()
```

Out[11]:

	age	annual Salary	credit card debt	net worth	car purchase amount
0	41.851720	62812.09301	11609.380910	238961.2505	35321.45877
1	40.870623	66646.89292	9572.957136	530973.9078	45115.52566
2	43.152897	53798.55112	11160.355060	638467.1773	42925.70921
3	58.271369	79370.03798	14426.164850	548599.0524	67422.36313
4	57.313749	59729.15130	5358.712177	560304.0671	55915.46248

Splitting: Train & Test Data

In [12]:
```
x=df.drop('car purchase amount', axis =1)
y=df['car purchase amount']
```

In [13]:
```
xtrain,xtest,ytrain,ytest = train_test_split(x,y, test_size =0.2, random_state =42)
```

In [14]:
```
#checking shapes of xtrain and xtest
xtrain.shape, xtest.shape
```

Out[14]: ((400, 4), (100, 4))

Scaling: StandardScaler

In [15]:
```
scaler =StandardScaler()
xtrain =scaler.fit_transform(xtrain)
xtest =scaler.transform(xtest)
```

In [16]:
```
xtrain, ytrain
```

Out[16]:
```
(array([[-1.22996274,  0.70264523,  0.06782569,  1.14322143],
        [-0.76993543, -0.49583563, -0.85967664, -1.16188481],
        [ 1.58484034, -0.55624875,  1.05701072,  0.76354398],
        ...,
        [-0.08676592,  0.13289634, -1.67932755,  1.00304384],
        [ 1.48934693, -1.73041723, -0.39436898, -0.06165717],
        [-1.92977493,  0.53060764, -0.63911954, -0.15781448]]),
 249    46135.27233
 433    29519.56184
 19     54827.52403
 322    59625.02618
 332    25252.93221
           ...
 106    34803.82395
 270    12536.93842
 348    49348.88394
 435    42139.64528
 102    33640.73697
 Name: car purchase amount, Length: 400, dtype: float64)
```

Linear Regression

In [17]:
```
from sklearn.linear_model import LinearRegression
lr= LinearRegression()
lr.fit(xtrain, ytrain)
```
Out[17]:
```
▾ LinearRegression
LinearRegression()
```
In [18]:
```
train_pred_lr = lr.predict(xtrain)
test_pred_lr =lr.predict(xtest)
```
In [19]:
```
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error

print('Training metrics')
print('r2_score: ',r2_score(ytrain,train_pred_lr))
print('mean_absolute_error: ',mean_absolute_error(ytrain,train_pred_lr))
print('root_mean_squared_error: ',np.sqrt(mean_squared_error(ytrain,train_pred_lr)))
print("\n")
print('Testing metrics')
print('r2_score: ',r2_score(ytest,test_pred_lr))
print('mean_absolute_error: ',mean_absolute_error(ytest,test_pred_lr))
print('root_mean_squared_error: ',np.sqrt(mean_squared_error(ytest,test_pred_lr)))
```
```
Training metrics
r2_score:  0.9999999812450086
mean_absolute_error:  1.1786832998436239
root_mean_squared_error:  1.4841461164361365


Testing metrics
r2_score:  0.9999999808303804
mean_absolute_error:  1.150084345075993
root_mean_squared_error:  1.4386814760274969
```
In [20]:
```
# Lets make some predicitons from the model using our test set
xtest.shape
```
Out[20]: (100, 4)

In [21]:
```
# predicting sales for 3 random records from xtest
import random
x1=random.randint(0,99)
x2=random.randint(0,99)
x3=random.randint(0,99)
x1,x2,x3
```
Out[21]: (18, 91, 2)

In [22]:
```
print('Predicted value, True Value')
print(lr.predict([xtest[x1]])," , ",ytest.values[x1])
print(lr.predict([xtest[x2]])," , ",ytest.values[x2])
print(lr.predict([xtest[x3]])," , ",ytest.values[x3])
```
```
Predicted value, True Value
[60528.35785327]  ,  60526.97788
[37365.80638491]  ,  37364.23474
[63081.63339589]  ,  63079.84329
```

Regression using ANN

ANN_Model_Development

In [23]:
```
sc_y=StandardScaler()
ytrain_scaled=sc_y.fit_transform(ytrain.values.reshape(-1, 1))
ytest_scaled=sc_y.transform(ytest.values.reshape(-1, 1))
```

ANN_Architecture

In [24]:
```
model = Sequential()
model.add(Dense(128, activation='relu', input_dim=4))   # input layer no. of neurons = inut dimensions
model.add(Dense(64, activation='relu'))                 # hidden layer
model.add(Dense(1, activation='linear'))                # regression ouput layer
```
```
E:\anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

https://keras.io/api/losses/ (https://keras.io/api/losses/)

https://keras.io/api/optimizers/ (https://keras.io/api/optimizers/)

https://keras.io/api/metrics/ (https://keras.io/api/metrics/)

In [25]:
```
model.compile(optimizer ='adam', loss= "mse", metrics =["r2_score"])
model.summary()
```
Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 128)	640
dense_1 (Dense)	(None, 64)	8,256
dense_2 (Dense)	(None, 1)	65

Total params: 8,961 (35.00 KB)

Trainable params: 8,961 (35.00 KB)

Non-trainable params: 0 (0.00 B)

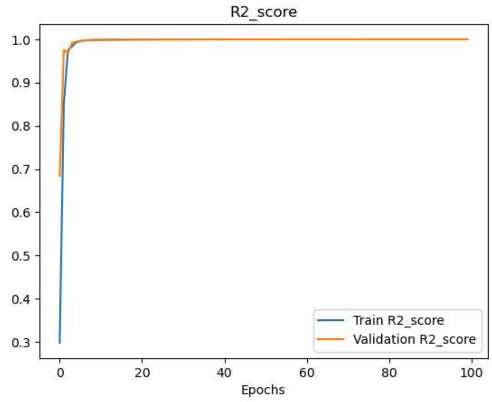
ANN_Model_Training

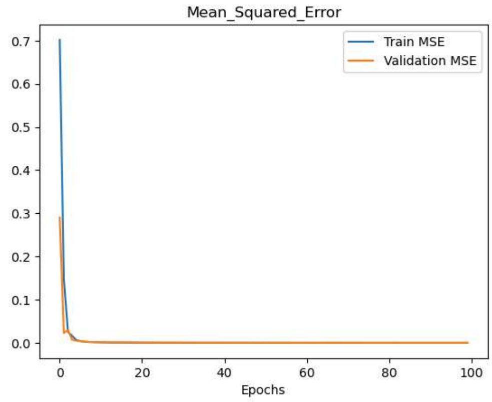
In [26]:
```python
history=model.fit(xtrain, ytrain_scaled, epochs=100, batch_size=32, validation_data=(xtest, ytest_scaled))
```

```
13/13 ━━━━━━━━━━━━━━━━━━━━ 2s 38ms/step - loss: 0.7923 - r2_score: 0.1274 - val_loss: 0.2902 - val_r2_score: 0.6843
Epoch 2/100
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.1990 - r2_score: 0.7871 - val_loss: 0.0226 - val_r2_score: 0.9754
Epoch 3/100
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0231 - r2_score: 0.9756 - val_loss: 0.0297 - val_r2_score: 0.9677
Epoch 4/100
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.0210 - r2_score: 0.9783 - val_loss: 0.0072 - val_r2_score: 0.9922
Epoch 5/100
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0067 - r2_score: 0.9932 - val_loss: 0.0050 - val_r2_score: 0.9946
Epoch 6/100
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.0045 - r2_score: 0.9953 - val_loss: 0.0039 - val_r2_score: 0.9958
Epoch 7/100
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step - loss: 0.0025 - r2_score: 0.9973 - val_loss: 0.0027 - val_r2_score: 0.9971
Epoch 8/100
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - loss: 0.0020 - r2_score: 0.9979 - val_loss: 0.0019 - val_r2_score: 0.9980
Epoch 9/100
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - loss: 0.0016 - r2_score: 0.9983 - val_loss: 0.0018 - val_r2_score: 0.9980
Epoch 10/100
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step - loss: 0.0013 - r2_score: 0.9987 - val_loss: 0.0014 - val_r2_score: 0.9984
Epoch 11/100
```

In [27]:
```python
# Plot accuracy and loss
import matplotlib.pyplot as plt
plt.plot(history.history['r2_score'], label='Train R2_score')
plt.plot(history.history['val_r2_score'], label='Validation R2_score')
plt.legend()
plt.title('R2_score')
plt.xlabel("Epochs")
plt.show()

# Similar plot for loss
plt.plot(history.history['loss'], label='Train MSE')
plt.plot(history.history['val_loss'], label='Validation MSE')
plt.legend()
plt.title("Mean_Squared_Error")
plt.xlabel("Epochs")
plt.show()
```





Model_Evaluation

Evaluate the Model on Train Data

In [28]:
```python
loss, accuracy = model.evaluate(xtrain, ytrain_scaled)
loss= np.sqrt(loss)
print(f'Train loss (RMSE): {loss:.8f}')
print(f'Train R2_score: {accuracy:.8f}')
```

```
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2.8115e-05 - r2_score: 1.0000
Train loss (RMSE): 0.00538407
Train R2_score: 0.99997103
```

Evaluate the Model on Test Data

In [29]:
```python
loss, accuracy = model.evaluate(xtest, ytest_scaled)
loss= np.sqrt(loss)
print(f'Test loss (RMSE): {loss:.8f}')
print(f'Test R2_score: {accuracy:.8f}')
```

```
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 1.8469e-04 - r2_score: 0.9998
Test loss (RMSE): 0.01307175
Test R2_score: 0.99981415
```

ANN_Model_Predictions

In [30]:
```python
train_pred=model.predict(xtrain)
test_pred=model.predict(xtest)
```

```
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
```

In [31]:

```
from sklearn.metrics import mean_squared_error, mean_absolute_error,r2_score

print('Training metrics')
print('r2_score: ',r2_score(ytrain_scaled,train_pred))
print('mean_absolute_error: ',mean_absolute_error(ytrain_scaled,train_pred))
print('root_mean_squared_error: ',np.sqrt(mean_squared_error(ytrain_scaled,train_pred)))
print("\n")
print('Testing metrics')
print('r2_score: ',r2_score(ytest_scaled,test_pred))
print('mean_absolute_error: ',mean_absolute_error(ytest_scaled,test_pred))
print('root_mean_squared_error: ',np.sqrt(mean_squared_error(ytest_scaled,test_pred)))
```

```
Training metrics
r2_score:  0.9999710118285393
mean_absolute_error:  0.004353657816639673
root_mean_squared_error:  0.005384066442816327


Testing metrics
r2_score:  0.9998141391065621
mean_absolute_error:  0.0099580186688057
root_mean_squared_error:  0.013071748712054968
```

The Result of Comparison of Metrics from LinearRegression vs ANN models is as follows

Linear Regression Metrics	ANN Metrics with "Adam" optimizer (Dense 128,64,1; relu,relu, linear, loss= mse, epoch=100, batch_size=32)
Training metrics	Training metrics
r2_score: 0.9999999812450086	r2_score: 0.9999710118285393
mean_absolute_error: 1.1786832998436239	mean_absolute_error: 0.004353657816639673
root_mean_squared_error: 1.4841461164361365	root_mean_squared_error: 0.005384066442816327
Testing metrics	Testing metrics
r2_score: 0.9999999808303804	r2_score: 0.9998141391065621
mean_absolute_error: 1.150084345075993	mean_absolute_error: 0.0099580186688057
root_mean_squared_error: 1.4386814760274969	root_mean_squared_error: 0.013071748712054968

In [32]:

```
# Inverse transform the Scaled y-class
test_pred_inverse_scaled = sc_y.inverse_transform(test_pred)
test_origianl_inverse_scaled =sc_y.inverse_transform(ytest_scaled)
```

In [33]:

```
test_pred_inverse_scaled.flatten()
```

Out[33]:

```
array([46301.94 , 45081.363, 62819.31 , 31407.738, 60650.36 , 63035.918,
       52843.62 , 54852.766, 52729.184, 48139.17 , 38149.965, 56417.293,
       44267.953, 38990.17 , 40175.65 , 54942.035, 48837.58 , 17505.602,
       60648.652, 50074.742, 41369.906, 52720.11 , 51741.387, 38078.61 ,
       41339.816, 38143.64 , 64157.727, 48101.9  , 22661.775, 52174.535,
       55265.953, 46006.94 , 40935.598, 57512.434, 42756.11 , 39949.684,
       61512.19 , 30691.66 , 42352.727, 40278.004, 57289.906, 60762.32 ,
       47718.94 , 36630.51 , 53517.234, 44499.527, 35197.043, 42264.37 ,
       51798.645, 47159.625, 41804.05 , 32870.65 , 38236.47 , 41844.18 ,
       45166.625, 47967.03 , 60189.58 , 44679.29 , 44439.49 , 38320.03 ,
       63963.996, 43414.242, 22543.998, 55216.293, 41527.23 , 54869.73 ,
       60042.137, 34244.875, 43018.71 , 47966.45 , 60333.277, 28829.725,
       59521.516, 55983.062, 59732.254, 22028.016, 41365.996, 49482.37 ,
       32887.582, 61464.97 , 42380.51 , 30448.46 , 35788.754, 43659.145,
       50725.285, 38867.51 , 38633.203, 30564.617, 40072.527, 35893.992,
       29619.246, 37323.63 , 30928.213, 40998.61 , 31956.775, 48995.785,
       45232.523, 51066.266, 43744.547, 52996.207], dtype=float32)
```

In [35]:

```
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
pd.DataFrame({"True": ytest, "predicted_LR": test_pred_lr,"True_inv_scaled":test_origianl_inverse_scaled.flatten(),"Pred_ANN_inv_scaled":test_pred_inverse_scaled.flatten()})
```

Out[35]:

	True	predicted_LR	True_inv_scaled	Pred_ANN_inv_scaled
361	46082.80993	46084.512762	46082.80993	46301.941406
73	45058.89690	45060.487047	45058.89690	45081.363281
374	63079.84329	63081.633396	63079.84329	62819.308594
155	31837.22537	31838.237987	31837.22537	31407.738281
104	60461.24268	60460.906486	60461.24268	60650.359375
394	63140.05082	63138.051326	63140.05082	63035.917969
377	52477.83479	52479.914562	52477.83479	52843.621094
124	54755.42038	54757.704680	54755.42038	54852.765625
68	52707.96816	52707.057176	52707.96816	52729.183594
450	47869.82593	47869.432488	47869.82593	48139.171875
9	38189.50601	38187.748588	38189.50601	38149.964844

Model Fine-Tuning:

We have not tuned this model as a generalized model has been achieved already with:

- Training R2_score = 0.999971
- Testing R2_score = 0.999814