In [1]:

```
import numpy as ny
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
pwd
```

Out[2]:

```
'C:\\Users\\soumik paul'
```

In [3]:

```
car_df=pd.read_csv('Car_Purchasing_Data.csv', encoding ='ISO-8859-1')
```

In [4]:

```
car_df
```

Out[4]:

	Customer Name	Customer e-mail	Country	Gender	Age	Annual Salary	Credit Card Debt	Net Wor
0	Martina Avila	cubilia.Curae.Phasellus@quisaccumsanconvallis.edu	Bulgaria	0	41.851720	62812.09301	11609.380910	238961.25
1	Harlan Barnes	eu.dolor@diam.co.uk	Belize	0	40.870623	66646.89292	9572.957136	530973.90
2	Naomi Rodriquez	vulputate.mauris.sagittis@ametconsectetueradip...	Algeria	1	43.152897	53798.55112	11160.355060	638467.17
3	Jade Cunningham	malesuada@dignissim.com	Cook Islands	1	58.271369	79370.03798	14426.164850	548599.05
4	Cedric Leach	felis.ullamcorper.viverra@egetmollislectus.net	Brazil	1	57.313749	59729.15130	5358.712177	560304.06
...	...	...	...	...	...	...	...	
495	Walter	ligula@Cumsociis.ca	Nepal	0	41.462515	71942.40291	6995.902524	541670.10
496	Vanna	Cum.sociis.natoque@Sedmolestie.edu	Zimbabwe	1	37.642000	56039.49793	12301.456790	360419.09
497	Pearl	penatibus.et@massanonante.com	Philippines	1	53.943497	68888.77805	10611.606860	764531.32
498	Nell	Quisque.varius@arcuVivamussit.net	Botswana	1	59.160509	49811.99062	14013.034510	337826.63
499	Marla	Camaron.marla@hotmail.com	marlal	1	46.731152	61370.67766	9391.341628	462946.49

500 rows × 9 columns

In [5]:

```
car_df.head(10)
```

Out[5]:

	Customer Name	Customer e-mail	Country	Gender	Age	Annual Salary	Credit Card Debt	Net Worth
0	Martina Avila	cubilia.Curae.Phasellus@quisaccumsanconvallis.edu	Bulgaria	0	41.851720	62812.09301	11609.380910	238961.2505
1	Harlan Barnes	eu.dolor@diam.co.uk	Belize	0	40.870623	66646.89292	9572.957136	530973.9078
2	Naomi Rodriquez	vulputate.mauris.sagittis@ametconsectetueradip...	Algeria	1	43.152897	53798.55112	11160.355060	638467.1773

	Customer Name	Customer e-mail	Country	Gender	Age	Annual Salary	Credit Card Debt	Net Worth
3	Cunningham	malesuada@dignissim.com	Cook Islands	1	58.271369	79370.03798	14426.164850	548599.0524
4	Cedric Leach	felis.ullamcorper.viverra@egetmollislectus.net	Brazil	1	57.313749	59729.15130	5358.712177	560304.0671
5	Carla Hester	mi@Aliquamerat.edu	Liberia	1	56.824893	68499.85162	14179.472440	428485.3604
6	Griffin Rivera	vehicula@at.co.uk	Syria	1	46.607315	39814.52200	5958.460188	326373.1812
7	Orli Casey	nunc.est.mollis@Suspendissetristiqueneque.co.uk	Czech Republic	1	50.193016	51752.23445	10985.696560	629312.4041
8	Marny Obrien	Phasellus@sedsemegestas.org	Armenia	0	46.584745	58139.25910	3440.823799	630059.0274
9	Rhonda Chavez	nec@nuncest.com	Somalia	1	43.323782	53457.10132	12884.078680	476643.3544

In [6]:

```
car_df.tail(5)
```

Out[6]:

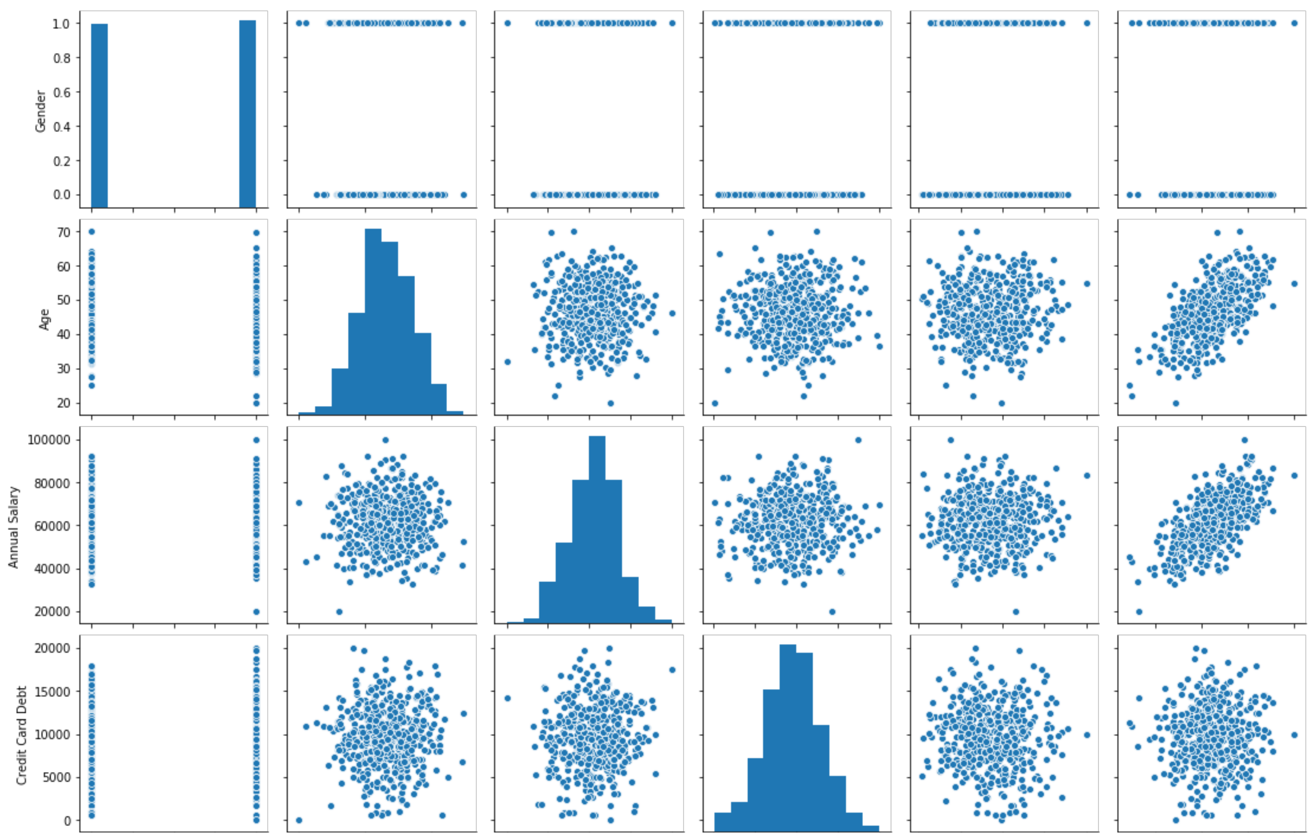
	Customer Name	Customer e-mail	Country	Gender	Age	Annual Salary	Credit Card Debt	Net Worth	Ca Purchas Amoun
495	Walter	ligula@Cumsociis.ca	Nepal	0	41.462515	71942.40291	6995.902524	541670.1016	48901.4434
496	Vanna	Cum.sociis.natoque@Sedmolestie.edu	Zimbabwe	1	37.642000	56039.49793	12301.456790	360419.0988	31491.4145
497	Pearl	penatibus.et@massanonante.com	Philippines	1	53.943497	68888.77805	10611.606860	764531.3203	64147.2888
498	Nell	Quisque.varius@arcuVivamussit.net	Botswana	1	59.160509	49811.99062	14013.034510	337826.6382	45442.1535
499	Marla	Camaron.marla@hotmail.com	marlal	1	46.731152	61370.67766	9391.341628	462946.4924	45107.2256

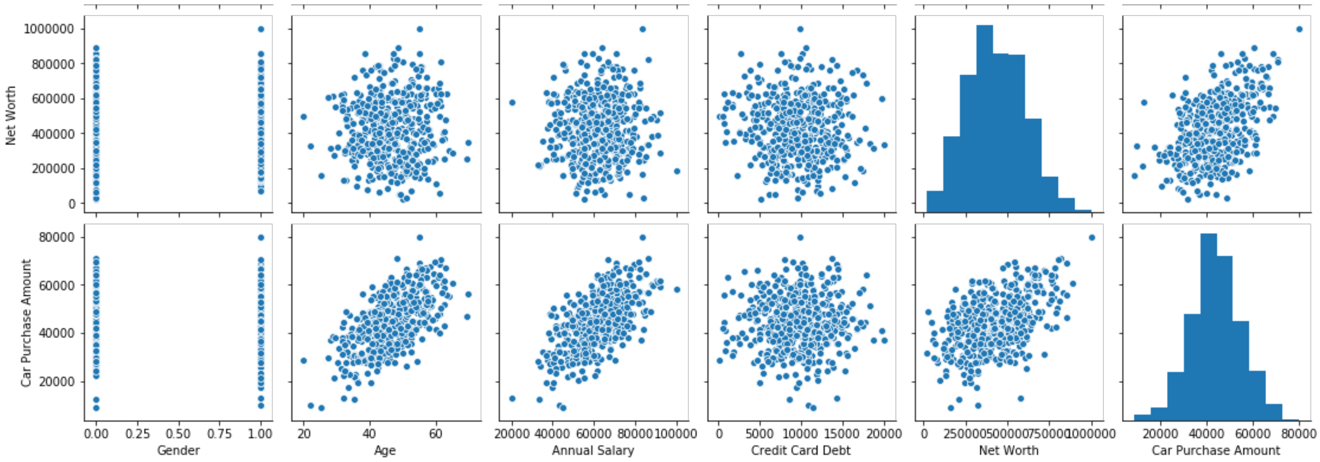
In [7]:

```
sns.pairplot(car_df)
```

Out[7]:

<seaborn.axisgrid.PairGrid at 0x15a284f6788>





In [8]:

```
X=car_df.drop(['Customer Name','Customer e-mail','Country','Car Purchase Amount'],axis=1)
```

In [9]:

```
X
```

Out[9]:

	Gender	Age	Annual Salary	Credit Card Debt	Net Worth
0	0	41.851720	62812.09301	11609.380910	238961.2505
1	0	40.870623	66646.89292	9572.957136	530973.9078
2	1	43.152897	53798.55112	11160.355060	638467.1773
3	1	58.271369	79370.03798	14426.164850	548599.0524
4	1	57.313749	59729.15130	5358.712177	560304.0671
...	...	...	...	...	...
495	0	41.462515	71942.40291	6995.902524	541670.1016
496	1	37.642000	56039.49793	12301.456790	360419.0988
497	1	53.943497	68888.77805	10611.606860	764531.3203
498	1	59.160509	49811.99062	14013.034510	337826.6382
499	1	46.731152	61370.67766	9391.341628	462946.4924

500 rows × 5 columns

In [10]:

```
y=car_df['Car Purchase Amount']
```

In [11]:

```
y
```

Out[11]:

```
0      35321.45877
1      45115.52566
2      42925.70921
3      67422.36313
4      55915.46248
          ...
495    48901.44342
496    31491.41457
497    64147.28888
498    45442.15353
499    45107.22566
Name: Car Purchase Amount, Length: 500, dtype: float64
```

In [12]:

```
X.shape
```

Out[12]:

```
(500, 5)
```

In [13]:

```
y.shape
```

Out[13]:

```
(500,)
```

In [14]:

```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
X_scaled=scaler.fit_transform(X)
```

In [15]:

```
X_scaled
```

Out[15]:

```
array([[0.        , 0.4370344 , 0.53515116, 0.57836085, 0.22342985],
       [0.        , 0.41741247, 0.58308616, 0.476028  , 0.52140195],
       [1.        , 0.46305795, 0.42248189, 0.55579674, 0.63108896],
       ...,
       [1.        , 0.67886994, 0.61110973, 0.52822145, 0.75972584],
       [1.        , 0.78321017, 0.37264988, 0.69914746, 0.3243129 ],
       [1.        , 0.53462305, 0.51713347, 0.46690159, 0.45198622]])
```

In [16]:

```
X_scaled.shape
```

Out[16]:

```
(500, 5)
```

In [17]:

```
scaler.data_max_
```

Out[17]:

```
array([1.e+00, 7.e+01, 1.e+05, 2.e+04, 1.e+06])
```

In [18]:

```
scaler.data_min_
```

Out[18]:

```
array([    0.,    20., 20000.,   100., 20000.])
```

In [19]:

```
y=y.values.reshape(-1,1)
```

In [20]:

```
y_scaled=scaler.fit_transform(y)
```

In [21]:

```
y_scaled
```

Out[21]:

```
array([[0.37072477],
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       [0.55076214],
```

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```

In [22]:

```
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)
```

In [23]:

```
X_train.shape
```

Out[23]:

```
(375, 5)
```

In [24]:

```
X_test.shape
```

Out[24]:

```
(125, 5)
```

In [25]:

```
import tensorflow.keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

model = Sequential()
model.add(Dense(8, input_dim=5, activation='relu'))
model.add(Dense(8, activation='relu'))
model.add(Dense(1, activation='linear'))
```

In [26]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 8)                 48
_________________________________________________________________
dense_1 (Dense)              (None, 8)                 72
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 9
=================================================================
Total params: 129
Trainable params: 129
Non-trainable params: 0
_________________________________________________________________
```

In [27]:

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

In [28]:

```
epoch_hist=model.fit(X_train,y_train, epochs=100,batch_size=50,verbose=1,validation_split=0.2)
```

```
Train on 300 samples, validate on 75 samples
Epoch 1/100
300/300 [==============================] - 0s 2ms/sample - loss: 0.2061 - val_loss: 0.1671
Epoch 2/100
300/300 [==============================] - 0s 123us/sample - loss: 0.1409 - val_loss: 0.1126
Epoch 3/100
300/300 [==============================] - 0s 151us/sample - loss: 0.0926 - val_loss: 0.0731
Epoch 4/100
300/300 [==============================] - 0s 136us/sample - loss: 0.0582 - val_loss: 0.0466
Epoch 5/100
300/300 [==============================] - 0s 90us/sample - loss: 0.0365 - val_loss: 0.0298
Epoch 6/100
300/300 [==============================] - 0s 93us/sample - loss: 0.0223 - val_loss: 0.0200
Epoch 7/100
300/300 [==============================] - 0s 73us/sample - loss: 0.0147 - val_loss: 0.0145
Epoch 8/100
300/300 [==============================] - 0s 156us/sample - loss: 0.0108 - val_loss: 0.0116
Epoch 9/100
300/300 [==============================] - 0s 93us/sample - loss: 0.0088 - val_loss: 0.0101
Epoch 10/100
300/300 [==============================] - 0s 113us/sample - loss: 0.0079 - val_loss: 0.0094
Epoch 11/100
300/300 [==============================] - 0s 103us/sample - loss: 0.0074 - val_loss: 0.0090
Epoch 12/100
300/300 [==============================] - 0s 113us/sample - loss: 0.0071 - val_loss: 0.0088
Epoch 13/100
300/300 [==============================] - 0s 106us/sample - loss: 0.0068 - val_loss: 0.0085
Epoch 14/100
300/300 [==============================] - 0s 113us/sample - loss: 0.0065 - val_loss: 0.0083
Epoch 15/100
300/300 [==============================] - 0s 113us/sample - loss: 0.0063 - val_loss: 0.0081
Epoch 16/100
300/300 [==============================] - 0s 83us/sample - loss: 0.0060 - val_loss: 0.0079
Epoch 17/100
300/300 [==============================] - 0s 113us/sample - loss: 0.0057 - val_loss: 0.0077
Epoch 18/100
300/300 [==============================] - 0s 116us/sample - loss: 0.0055 - val_loss: 0.0075
```

```
Epoch 19/100
300/300 [==============================] - 0s 80us/sample - loss: 0.0053 - val_loss: 0.0073
Epoch 20/100
300/300 [==============================] - 0s 106us/sample - loss: 0.0051 - val_loss: 0.0071
Epoch 21/100
300/300 [==============================] - 0s 90us/sample - loss: 0.0049 - val_loss: 0.0069
Epoch 22/100
300/300 [==============================] - 0s 66us/sample - loss: 0.0048 - val_loss: 0.0068
Epoch 23/100
300/300 [==============================] - 0s 76us/sample - loss: 0.0046 - val_loss: 0.0067
Epoch 24/100
300/300 [==============================] - 0s 76us/sample - loss: 0.0045 - val_loss: 0.0065
Epoch 25/100
300/300 [==============================] - 0s 86us/sample - loss: 0.0044 - val_loss: 0.0064
Epoch 26/100
300/300 [==============================] - 0s 63us/sample - loss: 0.0043 - val_loss: 0.0063
Epoch 27/100
300/300 [==============================] - 0s 73us/sample - loss: 0.0042 - val_loss: 0.0062
Epoch 28/100
300/300 [==============================] - 0s 96us/sample - loss: 0.0041 - val_loss: 0.0061
Epoch 29/100
300/300 [==============================] - 0s 103us/sample - loss: 0.0040 - val_loss: 0.0061
Epoch 30/100
300/300 [==============================] - 0s 90us/sample - loss: 0.0039 - val_loss: 0.0060
Epoch 31/100
300/300 [==============================] - 0s 83us/sample - loss: 0.0039 - val_loss: 0.0059
Epoch 32/100
300/300 [==============================] - 0s 68us/sample - loss: 0.0038 - val_loss: 0.0058
Epoch 33/100
300/300 [==============================] - 0s 90us/sample - loss: 0.0038 - val_loss: 0.0058
Epoch 34/100
300/300 [==============================] - 0s 83us/sample - loss: 0.0037 - val_loss: 0.0057
Epoch 35/100
300/300 [==============================] - 0s 110us/sample - loss: 0.0037 - val_loss: 0.0057
Epoch 36/100
300/300 [==============================] - 0s 153us/sample - loss: 0.0036 - val_loss: 0.0056
Epoch 37/100
300/300 [==============================] - 0s 173us/sample - loss: 0.0036 - val_loss: 0.0055
Epoch 38/100
300/300 [==============================] - 0s 163us/sample - loss: 0.0035 - val_loss: 0.0055
Epoch 39/100
300/300 [==============================] - 0s 153us/sample - loss: 0.0035 - val_loss: 0.0054
Epoch 40/100
300/300 [==============================] - 0s 126us/sample - loss: 0.0034 - val_loss: 0.0054
Epoch 41/100
300/300 [==============================] - 0s 176us/sample - loss: 0.0034 - val_loss: 0.0053
Epoch 42/100
300/300 [==============================] - 0s 199us/sample - loss: 0.0034 - val_loss: 0.0053
Epoch 43/100
300/300 [==============================] - 0s 127us/sample - loss: 0.0033 - val_loss: 0.0052
Epoch 44/100
300/300 [==============================] - 0s 143us/sample - loss: 0.0033 - val_loss: 0.0052
Epoch 45/100
300/300 [==============================] - 0s 93us/sample - loss: 0.0033 - val_loss: 0.0051
Epoch 46/100
300/300 [==============================] - 0s 95us/sample - loss: 0.0032 - val_loss: 0.0051
Epoch 47/100
300/300 [==============================] - 0s 73us/sample - loss: 0.0032 - val_loss: 0.0050
Epoch 48/100
300/300 [==============================] - 0s 96us/sample - loss: 0.0032 - val_loss: 0.0050
Epoch 49/100
300/300 [==============================] - 0s 88us/sample - loss: 0.0031 - val_loss: 0.0049
Epoch 50/100
300/300 [==============================] - 0s 66us/sample - loss: 0.0031 - val_loss: 0.0049
Epoch 51/100
300/300 [==============================] - 0s 90us/sample - loss: 0.0031 - val_loss: 0.0048
Epoch 52/100
300/300 [==============================] - 0s 73us/sample - loss: 0.0030 - val_loss: 0.0048
Epoch 53/100
300/300 [==============================] - 0s 86us/sample - loss: 0.0030 - val_loss: 0.0047
Epoch 54/100
300/300 [==============================] - 0s 76us/sample - loss: 0.0030 - val_loss: 0.0047
Epoch 55/100
300/300 [==============================] - 0s 53us/sample - loss: 0.0029 - val_loss: 0.0047
Epoch 56/100
300/300 [==============================] - 0s 76us/sample - loss: 0.0029 - val_loss: 0.0046
Epoch 57/100
```

```
300/300 [==============================] - 0s 66us/sample - loss: 0.0029 - val_loss: 0.0046
Epoch 58/100
300/300 [==============================] - 0s 66us/sample - loss: 0.0029 - val_loss: 0.0045
Epoch 59/100
300/300 [==============================] - 0s 86us/sample - loss: 0.0028 - val_loss: 0.0045
Epoch 60/100
300/300 [==============================] - 0s 83us/sample - loss: 0.0028 - val_loss: 0.0044
Epoch 61/100
300/300 [==============================] - ETA: 0s - loss: 0.002 - 0s 120us/sample - loss: 0.0028
- val_loss: 0.0044
Epoch 62/100
300/300 [==============================] - 0s 133us/sample - loss: 0.0028 - val_loss: 0.0044
Epoch 63/100
300/300 [==============================] - 0s 120us/sample - loss: 0.0027 - val_loss: 0.0043
Epoch 64/100
300/300 [==============================] - 0s 83us/sample - loss: 0.0027 - val_loss: 0.0043
Epoch 65/100
300/300 [==============================] - 0s 63us/sample - loss: 0.0027 - val_loss: 0.0042
Epoch 66/100
300/300 [==============================] - 0s 80us/sample - loss: 0.0026 - val_loss: 0.0042
Epoch 67/100
300/300 [==============================] - 0s 66us/sample - loss: 0.0026 - val_loss: 0.0042
Epoch 68/100
300/300 [==============================] - 0s 86us/sample - loss: 0.0026 - val_loss: 0.0041
Epoch 69/100
300/300 [==============================] - 0s 63us/sample - loss: 0.0026 - val_loss: 0.0041
Epoch 70/100
300/300 [==============================] - 0s 73us/sample - loss: 0.0025 - val_loss: 0.0041
Epoch 71/100
300/300 [==============================] - 0s 76us/sample - loss: 0.0025 - val_loss: 0.0040
Epoch 72/100
300/300 [==============================] - 0s 100us/sample - loss: 0.0025 - val_loss: 0.0040
Epoch 73/100
300/300 [==============================] - 0s 103us/sample - loss: 0.0025 - val_loss: 0.0039
Epoch 74/100
300/300 [==============================] - 0s 100us/sample - loss: 0.0024 - val_loss: 0.0039
Epoch 75/100
300/300 [==============================] - 0s 86us/sample - loss: 0.0024 - val_loss: 0.0039
Epoch 76/100
300/300 [==============================] - 0s 80us/sample - loss: 0.0024 - val_loss: 0.0038
Epoch 77/100
300/300 [==============================] - 0s 80us/sample - loss: 0.0024 - val_loss: 0.0038
Epoch 78/100
300/300 [==============================] - 0s 60us/sample - loss: 0.0024 - val_loss: 0.0038
Epoch 79/100
300/300 [==============================] - 0s 70us/sample - loss: 0.0023 - val_loss: 0.0037
Epoch 80/100
300/300 [==============================] - 0s 73us/sample - loss: 0.0023 - val_loss: 0.0037
Epoch 81/100
300/300 [==============================] - 0s 60us/sample - loss: 0.0023 - val_loss: 0.0037
Epoch 82/100
300/300 [==============================] - 0s 57us/sample - loss: 0.0023 - val_loss: 0.0036
Epoch 83/100
300/300 [==============================] - 0s 53us/sample - loss: 0.0022 - val_loss: 0.0036
Epoch 84/100
300/300 [==============================] - 0s 76us/sample - loss: 0.0022 - val_loss: 0.0036
Epoch 85/100
300/300 [==============================] - 0s 80us/sample - loss: 0.0022 - val_loss: 0.0035
Epoch 86/100
300/300 [==============================] - 0s 70us/sample - loss: 0.0022 - val_loss: 0.0035
Epoch 87/100
300/300 [==============================] - 0s 60us/sample - loss: 0.0022 - val_loss: 0.0035
Epoch 88/100
300/300 [==============================] - 0s 60us/sample - loss: 0.0021 - val_loss: 0.0034
Epoch 89/100
300/300 [==============================] - 0s 57us/sample - loss: 0.0021 - val_loss: 0.0034
Epoch 90/100
300/300 [==============================] - 0s 63us/sample - loss: 0.0021 - val_loss: 0.0034
Epoch 91/100
300/300 [==============================] - 0s 60us/sample - loss: 0.0021 - val_loss: 0.0034
Epoch 92/100
300/300 [==============================] - 0s 60us/sample - loss: 0.0021 - val_loss: 0.0033
Epoch 93/100
300/300 [==============================] - 0s 70us/sample - loss: 0.0020 - val_loss: 0.0033
Epoch 94/100
300/300 [==============================] - 0s 70us/sample - loss: 0.0020 - val_loss: 0.0033
Epoch 95/100
```

```
300/300 [==============================] - 0s 63us/sample - loss: 0.0020 - val_loss: 0.0033
Epoch 96/100
300/300 [==============================] - 0s 66us/sample - loss: 0.0020 - val_loss: 0.0032
Epoch 97/100
300/300 [==============================] - 0s 83us/sample - loss: 0.0020 - val_loss: 0.0032
Epoch 98/100
300/300 [==============================] - 0s 76us/sample - loss: 0.0020 - val_loss: 0.0032
Epoch 99/100
300/300 [==============================] - 0s 100us/sample - loss: 0.0019 - val_loss: 0.0032
Epoch 100/100
300/300 [==============================] - 0s 96us/sample - loss: 0.0019 - val_loss: 0.0031
```

In [29]:

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

Out[29]:

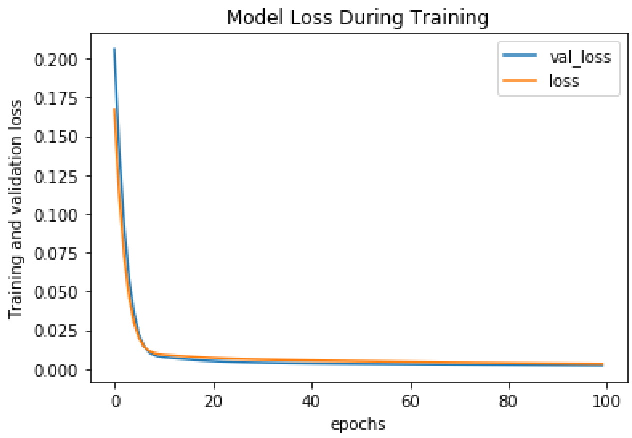
```
dict_keys(['loss', 'val_loss'])
```

In [30]:

```
plt.plot(epoch_hist.history['loss'])
plt.plot(epoch_hist.history['val_loss'])
plt.title('Model Loss During Training')
plt.ylabel('Training and validation loss')
plt.xlabel('epochs')
plt.legend(['val_loss','loss'])
```

Out[30]:

```
<matplotlib.legend.Legend at 0x15a31e09908>
```



In [31]:

```
X_test=ny.array([[0,40,53798,11160,638467]])
y_predict=model.predict(X_test)
```

In [32]:

```
print("expected output ",y_predict)
```

```
expected output  [[407137.97]]
```

In [ ]:

In [ ]: