Neural Network Assignment

Data Set - Gas_turbines

1. Import Necessary libraries

In [1]:
```
import pandas as pd
import numpy as np

from matplotlib import pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

2. Import Data

In [2]:
```
turbines_data = pd.read_csv('gas_turbines.csv')
turbines_data
```

Out[2]:

	AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	CDP	CO	NOX
0	6.8594	1007.9	96.799	3.5000	19.663	1059.2	550.00	114.70	10.605	3.1547	82.722
1	6.7850	1008.4	97.118	3.4998	19.728	1059.3	550.00	114.72	10.598	3.2363	82.776
2	6.8977	1008.8	95.939	3.4824	19.779	1059.4	549.87	114.71	10.601	3.2012	82.468
3	7.0569	1009.2	95.249	3.4805	19.792	1059.6	549.99	114.72	10.606	3.1923	82.670
4	7.3978	1009.7	95.150	3.4976	19.765	1059.7	549.98	114.72	10.612	3.2484	82.311
...	...	...	...	...	...	...	...	...	...	...	...
15034	9.0301	1005.6	98.460	3.5421	19.164	1049.7	546.21	111.61	10.400	4.5186	79.559
15035	7.8879	1005.9	99.093	3.5059	19.414	1046.3	543.22	111.78	10.433	4.8470	79.917
15036	7.2647	1006.3	99.496	3.4770	19.530	1037.7	537.32	110.19	10.483	7.9632	90.912
15037	7.0060	1006.8	99.008	3.4486	19.377	1043.2	541.24	110.74	10.533	6.2494	93.227
15038	6.9279	1007.2	97.533	3.4275	19.306	1049.9	545.85	111.58	10.583	4.9816	92.498

15039 rows × 11 columns

3. Data Understanding

3.1 Initial Analysis :

In [3]:
```
turbines_data.head()
```

Out[3]:

	AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	CDP	CO	NOX
0	6.8594	1007.9	96.799	3.5000	19.663	1059.2	550.00	114.70	10.605	3.1547	82.722
1	6.7850	1008.4	97.118	3.4998	19.728	1059.3	550.00	114.72	10.598	3.2363	82.776
2	6.8977	1008.8	95.939	3.4824	19.779	1059.4	549.87	114.71	10.601	3.2012	82.468
3	7.0569	1009.2	95.249	3.4805	19.792	1059.6	549.99	114.72	10.606	3.1923	82.670
4	7.3978	1009.7	95.150	3.4976	19.765	1059.7	549.98	114.72	10.612	3.2484	82.311

In [4]:
```
turbines_data.shape
```

Out[4]:
```
(15039, 11)
```

In [5]:
```
turbines_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15039 entries, 0 to 15038
Data columns (total 11 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   AT      15039 non-null  float64
 1   AP      15039 non-null  float64
 2   AH      15039 non-null  float64
 3   AFDP    15039 non-null  float64
 4   GTEP    15039 non-null  float64
 5   TIT     15039 non-null  float64
 6   TAT     15039 non-null  float64
 7   TEY     15039 non-null  float64
 8   CDP     15039 non-null  float64
 9   CO      15039 non-null  float64
 10  NOX     15039 non-null  float64
dtypes: float64(11)
memory usage: 1.3 MB
```

In [6]:
```
turbines_data.isna().sum()
```

Out[6]:
```
AT      0
AP      0
AH      0
AFDP    0
GTEP    0
TIT     0
TAT     0
TEY     0
CDP     0
CO      0
NOX     0
dtype: int64
```

In [7]:
```
turbines_data.describe()
```

Out[7]:

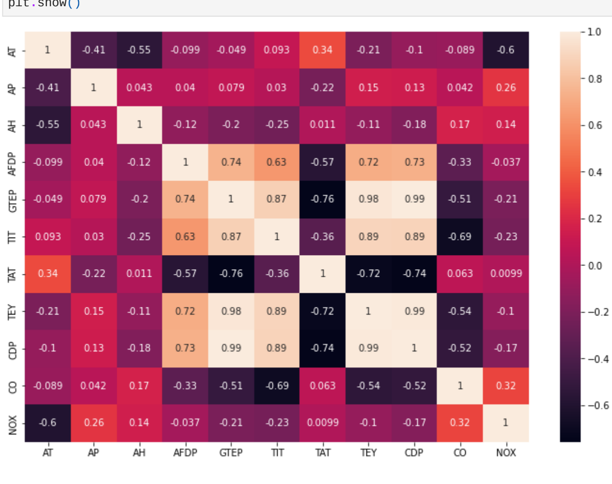
	AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	CDP	CO	NOX
count	15039.000000	15039.00000	15039.000000	15039.000000	15039.000000	15039.000000	15039.000000	15039.000000	15039.000000	15039.000000	15039.000000
mean	17.764381	1013.19924	79.124174	4.200294	25.419061	1083.798770	545.396183	134.188464	12.102353	1.972499	68.190934
std	7.574323	6.41076	13.793439	0.760197	4.173916	16.527806	7.866803	15.829717	1.103196	2.222206	10.470586
min	0.522300	985.85000	30.344000	2.087400	17.878000	1000.800000	512.450000	100.170000	9.904400	0.000388	27.765000
25%	11.408000	1008.90000	69.750000	3.723900	23.294000	1079.600000	542.170000	127.985000	11.622000	0.858055	61.303500
50%	18.186000	1012.80000	82.266000	4.186200	25.082000	1088.700000	549.890000	133.780000	12.025000	1.390200	66.601000
75%	23.862500	1016.90000	90.043500	4.550900	27.184000	1096.000000	550.060000	140.895000	12.578000	2.160400	73.935500
max	34.929000	1034.20000	100.200000	7.610600	37.402000	1100.800000	550.610000	174.610000	15.081000	44.103000	119.890000

In [8]:
```
turbines_data.dtypes
```

Out[8]:
```
AT      float64
AP      float64
AH      float64
AFDP    float64
GTEP    float64
TIT     float64
TAT     float64
TEY     float64
CDP     float64
CO      float64
NOX     float64
dtype: object
```

3.2 Correlation Matrix :

In [9]:
```
plt.figure(figsize = (12,8))
sns.heatmap(turbines_data.corr(),annot = True)
plt.show()
```

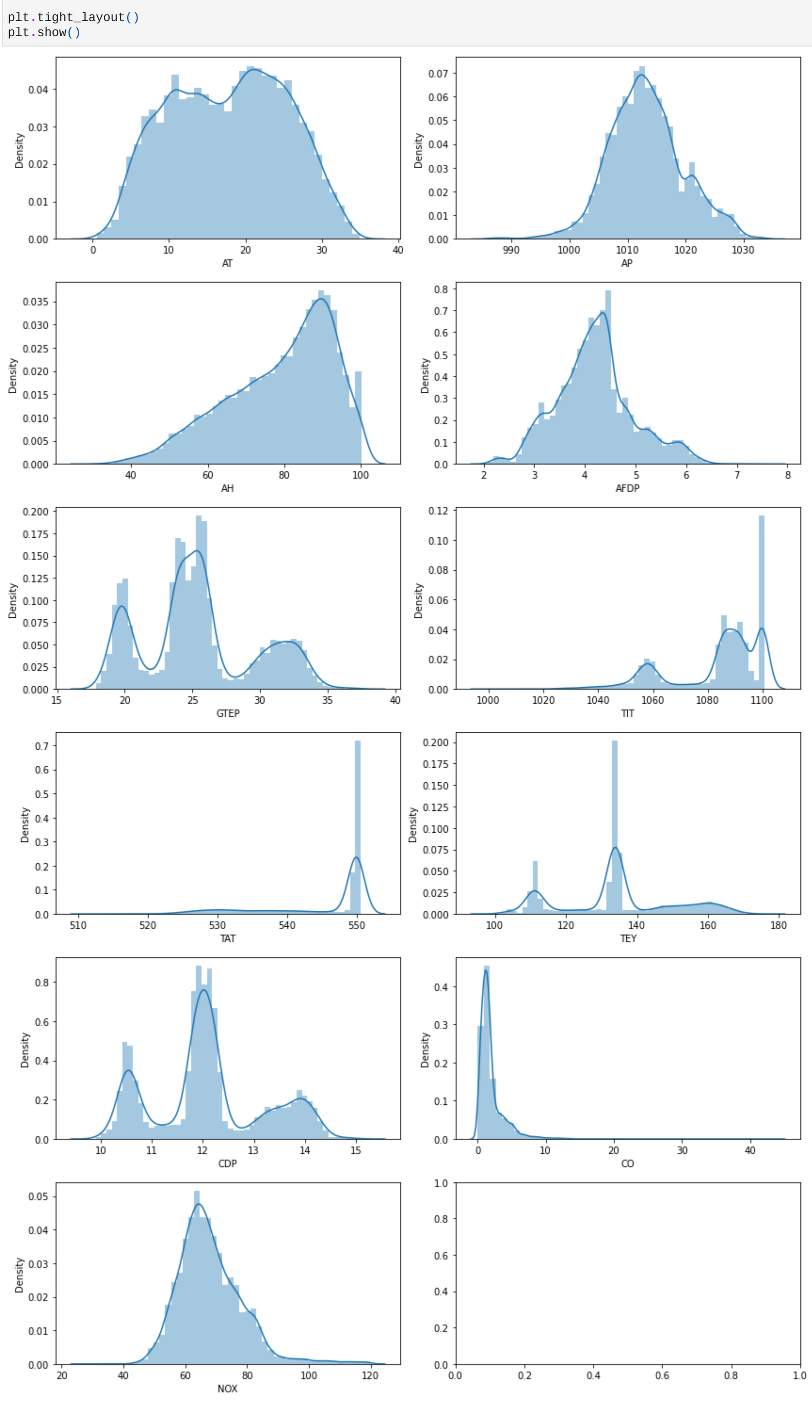


3.3 Visualization using distplot :

In [10]:
```
fig, ax = plt.subplots(6,2, figsize = (12,20))

sns.distplot(turbines_data.AT, ax = ax[0,0])
sns.distplot(turbines_data.AP, ax = ax[0,1])
sns.distplot(turbines_data.AH, ax = ax[1,0])
sns.distplot(turbines_data.AFDP, ax = ax[1,1])
sns.distplot(turbines_data.GTEP, ax = ax[2,0])
sns.distplot(turbines_data.TIT, ax = ax[2,1])
sns.distplot(turbines_data.TAT, ax = ax[3,0])
sns.distplot(turbines_data.TEY, ax = ax[3,1])
sns.distplot(turbines_data.CDP, ax = ax[4,0])
sns.distplot(turbines_data.CO, ax = ax[4,1])
sns.distplot(turbines_data.NOX, ax = ax[5,0])

plt.tight_layout()
plt.show()
```

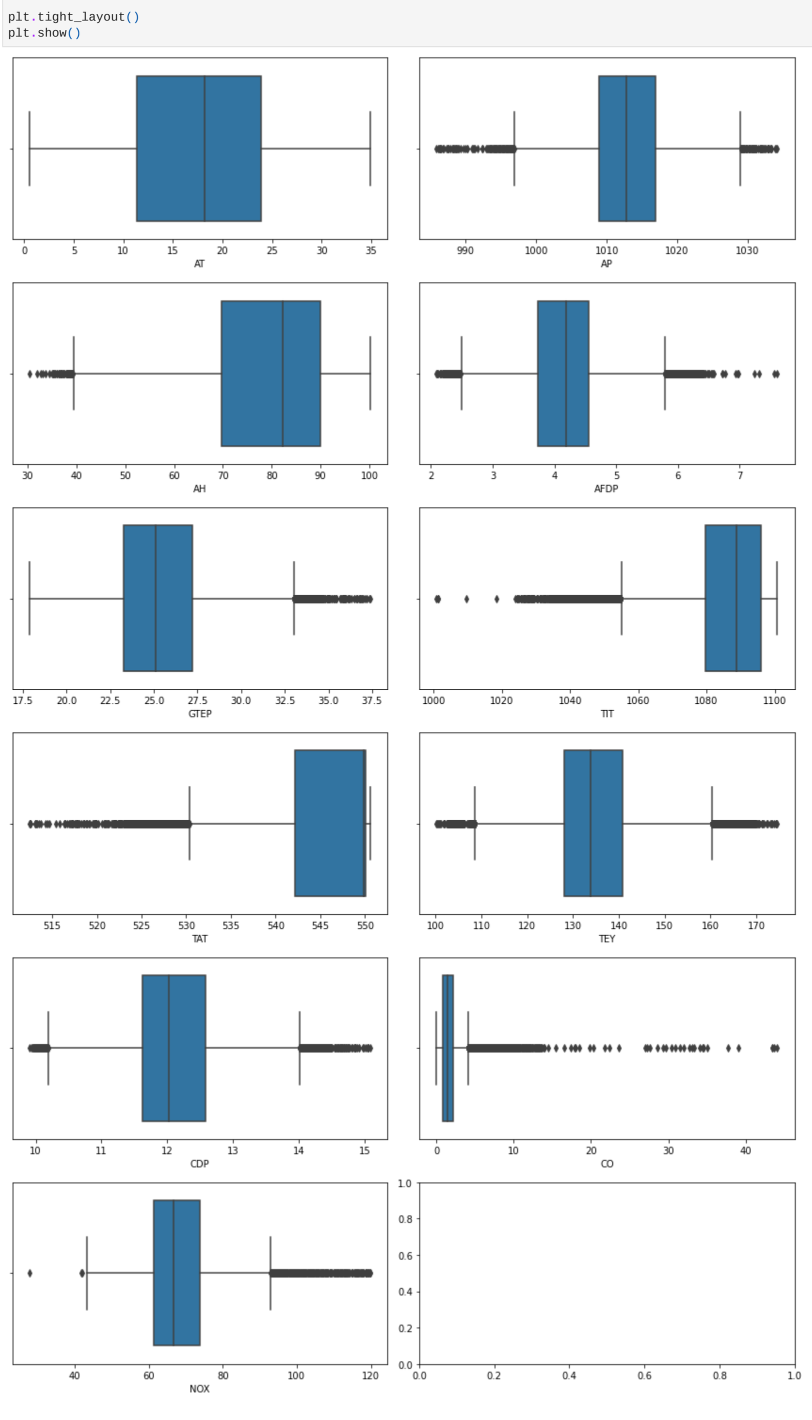


3.4 Checking of the outlier :

In [11]:
```
fig, ax = plt.subplots(6,2, figsize = (12,20))

sns.boxplot(turbines_data.AT, ax = ax[0,0])
sns.boxplot(turbines_data.AP, ax = ax[0,1])
sns.boxplot(turbines_data.AH, ax = ax[1,0])
sns.boxplot(turbines_data.AFDP, ax = ax[1,1])
sns.boxplot(turbines_data.GTEP, ax = ax[2,0])
sns.boxplot(turbines_data.TIT, ax = ax[2,1])
sns.boxplot(turbines_data.TAT, ax = ax[3,0])
sns.boxplot(turbines_data.TEY, ax = ax[3,1])
sns.boxplot(turbines_data.CDP, ax = ax[4,0])
sns.boxplot(turbines_data.CO, ax = ax[4,1])
sns.boxplot(turbines_data.NOX, ax = ax[5,0])

plt.tight_layout()
plt.show()
```



4. Extrating the independent and dependent variables

In [12]:
```
turbines_data["TEy"] = 1
turbines_data.loc[turbines_data["TEY"] > 135,"TEy"] = 2
turbines_data.drop(["TEY"],axis = 1,inplace = True)
```

In [13]:
```
x = np.array(turbines_data.iloc[:,0:10])
x
```

Out[13]:
```
array([[   6.8594, 1007.9   ,   96.799 , ...,   10.605 ,    3.1547,
          82.722 ],
       [   6.785 , 1008.4   ,   97.118 , ...,   10.598 ,    3.2363,
          82.776 ],
       [   6.8977, 1008.8   ,   95.939 , ...,   10.601 ,    3.2012,
          82.468 ],
       ...,
       [   7.2647, 1006.3   ,   99.496 , ...,   10.483 ,    7.9632,
          90.912 ],
       [   7.006 , 1006.8   ,   99.008 , ...,   10.533 ,    6.2494,
          93.227 ],
       [   6.9279, 1007.2   ,   97.533 , ...,   10.583 ,    4.9816,
          92.498 ]])
```

In [14]:
```
y = np.array(turbines_data.iloc[:,10])
y
```

Out[14]:
```
array([1, 1, 1, ..., 1, 1, 1], dtype=int64)
```

4.1 Normalizing data :

In [15]:
```
from sklearn.model_selection import train_test_split
```

In [16]:
```
def norm_func(i):
    x = (i-i.min())/(i.max()-i.min())
    return (x)
```

In [17]:
```
x_norm = norm_func(x)
```

4.2 Data Splitting :

In [18]:
```
x_train,x_test,y_train,y_test = train_test_split(x_norm,y, test_size = 0.2)
```

4.3 Applying Neural Network :

In [19]:
```
import keras.models
import tensorflow
from tensorflow.keras.models import Sequential
from keras.layers import Dense
```

In [20]:
```
model = Sequential()
```

In [21]:
```
# fix random seed for reproducibility
seed = 7
np.random.seed(seed)
```

In [22]:
```
model.add(Dense(8, input_dim = 10, kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dense(4,  kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dense(1,  kernel_initializer = 'uniform', activation = 'linear'))
```

In [23]:
```
model.compile(loss = 'mse', optimizer = 'adam', metrics = ['accuracy'])
```

In [24]:
```
model.fit(x_train,y_train, validation_split = 0.3, epochs = 50, batch_size = 10)
```

```
Epoch 1/50
843/843 [==============================] - 4s 3ms/step - loss: 1.0960 - accuracy: 0.2332 - val_loss: 0.5753 - val_accuracy: 0.6978
Epoch 2/50
843/843 [==============================] - 2s 3ms/step - loss: 0.3543 - accuracy: 0.7078 - val_loss: 0.2494 - val_accuracy: 0.6978
Epoch 3/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2175 - accuracy: 0.7078 - val_loss: 0.2129 - val_accuracy: 0.6978
Epoch 4/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2071 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 5/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 6/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 7/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 8/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 9/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2111 - val_accuracy: 0.6978
Epoch 10/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 11/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2111 - val_accuracy: 0.6978
Epoch 12/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 13/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 14/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2112 - val_accuracy: 0.6978
Epoch 15/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 16/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 17/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 18/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2114 - val_accuracy: 0.6978
Epoch 19/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 20/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 21/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 22/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 23/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 24/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2111 - val_accuracy: 0.6978
Epoch 25/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 26/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 27/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 28/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 29/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 30/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 31/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 32/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2111 - val_accuracy: 0.6978
Epoch 33/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2111 - val_accuracy: 0.6978
Epoch 34/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 35/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 36/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 37/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 38/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2111 - val_accuracy: 0.6978
Epoch 39/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2113 - val_accuracy: 0.6978
Epoch 40/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2111 - val_accuracy: 0.6978
Epoch 41/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 42/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 43/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 44/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 45/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 46/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 47/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2112 - val_accuracy: 0.6978
Epoch 48/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2111 - val_accuracy: 0.6978
Epoch 49/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2111 - val_accuracy: 0.6978
Epoch 50/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
```

Out[24]:
```
<keras.callbacks.History at 0x1cbeb3d28b0>
```

In [25]:
```
scores = model.evaluate(x_train, y_train)
print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
376/376 [==============================] - 1s 2ms/step - loss: 0.2081 - accuracy: 0.7048
accuracy: 70.48%
```

In [26]:
```
scores = model.evaluate(x_test, y_test)
print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
94/94 [==============================] - 0s 2ms/step - loss: 0.2113 - accuracy: 0.6968
accuracy: 69.68%
```

4.4 Visualize training history :

In [27]:
```
history = model.fit(x_train,y_train, validation_split = 0.3, epochs = 50, batch_size = 10)
```

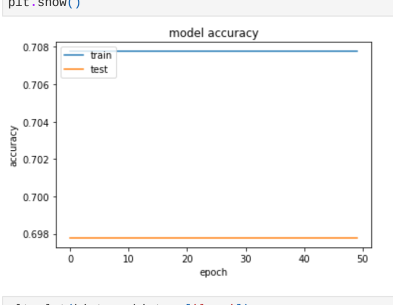
```
Epoch 1/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2111 - val_accuracy: 0.6978
Epoch 2/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 3/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 4/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 5/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2068 - accuracy: 0.7078 - val_loss: 0.2111 - val_accuracy: 0.6978
Epoch 6/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 7/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 8/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 9/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 10/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 11/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 12/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2112 - val_accuracy: 0.6978
Epoch 13/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 14/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2111 - val_accuracy: 0.6978
Epoch 15/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2112 - val_accuracy: 0.6978
Epoch 16/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2112 - val_accuracy: 0.6978
Epoch 17/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 18/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2114 - val_accuracy: 0.6978
Epoch 19/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 20/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2068 - accuracy: 0.7078 - val_loss: 0.2118 - val_accuracy: 0.6978
Epoch 21/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2115 - val_accuracy: 0.6978
Epoch 22/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 23/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 24/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 25/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2111 - val_accuracy: 0.6978
Epoch 26/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 27/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 28/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 29/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2113 - val_accuracy: 0.6978
Epoch 30/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 31/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2068 - accuracy: 0.7078 - val_loss: 0.2112 - val_accuracy: 0.6978
Epoch 32/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 33/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 34/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2112 - val_accuracy: 0.6978
Epoch 35/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 36/50
843/843 [==============================] - 3s 3ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 37/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2112 - val_accuracy: 0.6978
Epoch 38/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 39/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 40/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 41/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 42/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2110 - val_accuracy: 0.6978
Epoch 43/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 44/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2068 - accuracy: 0.7078 - val_loss: 0.2119 - val_accuracy: 0.6978
Epoch 45/50
843/843 [==============================] - 2s 2ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 46/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 47/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 48/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2069 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 49/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
Epoch 50/50
843/843 [==============================] - 2s 3ms/step - loss: 0.2070 - accuracy: 0.7078 - val_loss: 0.2109 - val_accuracy: 0.6978
```

In [28]:
```
# list all data in history
model.history.history.keys()
```

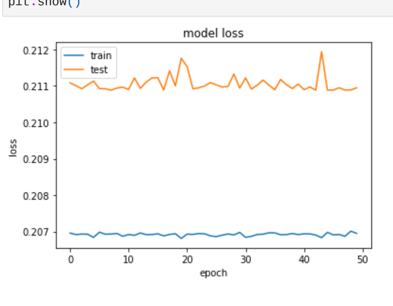
Out[28]:
```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

4.5 summarize history for accuracy and Loss :

In [29]:
```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train','test'], loc = 'upper left')
plt.show()
```



In [30]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train','test'], loc = 'upper left')
plt.show()
```



5. Tuning of Hyperparameter : Batch Size and Epochs

In [31]:
```
from sklearn.model_selection import GridSearchCV, KFold
from keras.wrappers.scikit_learn import KerasClassifier
from keras.optimizers import Adam
from tensorflow.keras.models import load_model
```

In [32]:
```
def create_model():
    model = Sequential()
    model.add(Dense(12, input_dim = 10, kernel_initializer = 'uniform', activation = 'relu'))
    model.add(Dense(8,  kernel_initializer = 'uniform', activation = 'relu'))
    model.add(Dense(1,  kernel_initializer = 'uniform', activation = 'linear'))

    adam = Adam(lr = 0.01)
    model.compile(loss = 'mse', optimizer = adam, metrics = ['accuracy'])
    return model
```

5.1 Create the model :

In [33]:
```
model_1 = KerasClassifier(build_fn = create_model,verbose = 0)
```

5.2 Define the grid search parameters :

In [34]:
```
batch_size = [10,20,40]
epochs = [10,50,100]
```

5.3 Make a dictionary of the grid search parameters :

In [35]:
```
param_grid = dict(batch_size = batch_size,epochs = epochs)
```

5.4 Build and fit the GridSearchCV :

In [36]:
```
grid = GridSearchCV(estimator = model_1, param_grid = param_grid,cv = KFold(),verbose = 10)
grid_result = grid.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits
[CV 1/5; 1/9] START batch_size=10, epochs=10....................................
[CV 1/5; 1/9] END .....batch_size=10, epochs=10;, score=0.708 total time=  15.0s
[CV 2/5; 1/9] START batch_size=10, epochs=10....................................
[CV 2/5; 1/9] END .....batch_size=10, epochs=10;, score=0.707 total time=  17.0s
[CV 3/5; 1/9] START batch_size=10, epochs=10....................................
[CV 3/5; 1/9] END .....batch_size=10, epochs=10;, score=0.714 total time=  17.0s
[CV 4/5; 1/9] START batch_size=10, epochs=10....................................
[CV 4/5; 1/9] END .....batch_size=10, epochs=10;, score=0.958 total time=  17.0s
[CV 5/5; 1/9] START batch_size=10, epochs=10....................................
[CV 5/5; 1/9] END .....batch_size=10, epochs=10;, score=0.696 total time=  17.3s
[CV 1/5; 2/9] START batch_size=10, epochs=50....................................
[CV 1/5; 2/9] END .....batch_size=10, epochs=50;, score=0.946 total time= 1.4min
[CV 2/5; 2/9] START batch_size=10, epochs=50....................................
[CV 2/5; 2/9] END .....batch_size=10, epochs=50;, score=0.707 total time= 1.4min
[CV 3/5; 2/9] START batch_size=10, epochs=50....................................
[CV 3/5; 2/9] END .....batch_size=10, epochs=50;, score=0.714 total time= 1.3min
[CV 4/5; 2/9] START batch_size=10, epochs=50....................................
[CV 4/5; 2/9] END .....batch_size=10, epochs=50;, score=0.954 total time= 1.3min
[CV 5/5; 2/9] START batch_size=10, epochs=50....................................
[CV 5/5; 2/9] END .....batch_size=10, epochs=50;, score=0.696 total time= 1.4min
[CV 1/5; 3/9] START batch_size=10, epochs=100...................................
[CV 1/5; 3/9] END ....batch_size=10, epochs=100;, score=0.708 total time= 1.5min
[CV 2/5; 3/9] START batch_size=10, epochs=100...................................
[CV 2/5; 3/9] END ....batch_size=10, epochs=100;, score=0.707 total time= 1.4min
[CV 3/5; 3/9] START batch_size=10, epochs=100...................................
[CV 3/5; 3/9] END ....batch_size=10, epochs=100;, score=0.714 total time= 1.4min
[CV 4/5; 3/9] START batch_size=10, epochs=100...................................
[CV 4/5; 3/9] END ....batch_size=10, epochs=100;, score=0.699 total time= 1.5min
[CV 5/5; 3/9] START batch_size=10, epochs=100...................................
[CV 5/5; 3/9] END ....batch_size=10, epochs=100;, score=0.949 total time= 1.4min
[CV 1/5; 4/9] START batch_size=20, epochs=10....................................
[CV 1/5; 4/9] END .....batch_size=20, epochs=10;, score=0.708 total time=   4.4s
[CV 2/5; 4/9] START batch_size=20, epochs=10....................................
[CV 2/5; 4/9] END .....batch_size=20, epochs=10;, score=0.707 total time=   5.0s
[CV 3/5; 4/9] START batch_size=20, epochs=10....................................
[CV 3/5; 4/9] END .....batch_size=20, epochs=10;, score=0.714 total time=   4.7s
[CV 4/5; 4/9] START batch_size=20, epochs=10....................................
[CV 4/5; 4/9] END .....batch_size=20, epochs=10;, score=0.898 total time=   4.8s
[CV 5/5; 4/9] START batch_size=20, epochs=10....................................
[CV 5/5; 4/9] END .....batch_size=20, epochs=10;, score=0.948 total time=   4.4s
[CV 1/5; 5/9] START batch_size=20, epochs=50....................................
[CV 1/5; 5/9] END .....batch_size=20, epochs=50;, score=0.947 total time=  18.8s
[CV 2/5; 5/9] START batch_size=20, epochs=50....................................
[CV 2/5; 5/9] END .....batch_size=20, epochs=50;, score=0.946 total time=  21.4s
[CV 3/5; 5/9] START batch_size=20, epochs=50....................................
[CV 3/5; 5/9] END .....batch_size=20, epochs=50;, score=0.961 total time=  23.9s
[CV 4/5; 5/9] START batch_size=20, epochs=50....................................
[CV 4/5; 5/9] END .....batch_size=20, epochs=50;, score=0.948 total time=  18.7s
[CV 5/5; 5/9] START batch_size=20, epochs=50....................................
[CV 5/5; 5/9] END .....batch_size=20, epochs=50;, score=0.921 total time=  18.1s
[CV 1/5; 6/9] START batch_size=20, epochs=100...................................
[CV 1/5; 6/9] END ....batch_size=20, epochs=100;, score=0.948 total time=  37.3s
[CV 2/5; 6/9] START batch_size=20, epochs=100...................................
[CV 2/5; 6/9] END ....batch_size=20, epochs=100;, score=0.931 total time=  36.3s
[CV 3/5; 6/9] START batch_size=20, epochs=100...................................
[CV 3/5; 6/9] END ....batch_size=20, epochs=100;, score=0.947 total time=  36.8s
[CV 4/5; 6/9] START batch_size=20, epochs=100...................................
[CV 4/5; 6/9] END ....batch_size=20, epochs=100;, score=0.972 total time=  35.0s
[CV 5/5; 6/9] START batch_size=20, epochs=100...................................
[CV 5/5; 6/9] END ....batch_size=20, epochs=100;, score=0.696 total time=  36.8s
[CV 1/5; 7/9] START batch_size=40, epochs=10....................................
[CV 1/5; 7/9] END .....batch_size=40, epochs=10;, score=0.951 total time=   2.9s
[CV 2/5; 7/9] START batch_size=40, epochs=10....................................
[CV 2/5; 7/9] END .....batch_size=40, epochs=10;, score=0.937 total time=   2.4s
[CV 3/5; 7/9] START batch_size=40, epochs=10....................................
[CV 3/5; 7/9] END .....batch_size=40, epochs=10;, score=0.923 total time=   2.4s
[CV 4/5; 7/9] START batch_size=40, epochs=10....................................
[CV 4/5; 7/9] END .....batch_size=40, epochs=10;, score=0.938 total time=   2.4s
[CV 5/5; 7/9] START batch_size=40, epochs=10....................................
[CV 5/5; 7/9] END .....batch_size=40, epochs=10;, score=0.926 total time=   2.4s
[CV 1/5; 8/9] START batch_size=40, epochs=50....................................
[CV 1/5; 8/9] END .....batch_size=40, epochs=50;, score=0.950 total time=  10.1s
[CV 2/5; 8/9] START batch_size=40, epochs=50....................................
[CV 2/5; 8/9] END .....batch_size=40, epochs=50;, score=0.946 total time=  10.1s
[CV 3/5; 8/9] START batch_size=40, epochs=50....................................
[CV 3/5; 8/9] END .....batch_size=40, epochs=50;, score=0.942 total time=  10.4s
[CV 4/5; 8/9] START batch_size=40, epochs=50....................................
[CV 4/5; 8/9] END .....batch_size=40, epochs=50;, score=0.956 total time=   9.8s
[CV 5/5; 8/9] START batch_size=40, epochs=50....................................
[CV 5/5; 8/9] END .....batch_size=40, epochs=50;, score=0.933 total time=  10.3s
[CV 1/5; 9/9] START batch_size=40, epochs=100...................................
[CV 1/5; 9/9] END ....batch_size=40, epochs=100;, score=0.926 total time=  20.5s
[CV 2/5; 9/9] START batch_size=40, epochs=100...................................
[CV 2/5; 9/9] END ....batch_size=40, epochs=100;, score=0.707 total time=  19.7s
[CV 3/5; 9/9] START batch_size=40, epochs=100...................................
[CV 3/5; 9/9] END ....batch_size=40, epochs=100;, score=0.941 total time=  19.3s
[CV 4/5; 9/9] START batch_size=40, epochs=100...................................
[CV 4/5; 9/9] END ....batch_size=40, epochs=100;, score=0.968 total time=  19.8s
[CV 5/5; 9/9] START batch_size=40, epochs=100...................................
[CV 5/5; 9/9] END ....batch_size=40, epochs=100;, score=0.944 total time=  19.9s
```

Conclusion :

```
For Train Model we got 70.48% Accuracy
For Test Model we got 69.68% Accuracy
```