Aritificial Neural Network-02

```
In [2]:
         #Import Necessary Libraries
         import pandas as pd
         import numpy as np
         import tensorflow
         from sklearn.metrics import accuracy score, confusion matrix
         from sklearn.model selection import train test split , cross val score
         #Create your first NLP in keras
         from keras.models import Sequential
         from keras.layers import Dense
         from matplotlib import pyplot as plt
In [3]: | data = pd.read csv('gas turbines.csv')
         data
Out[3]:
                    AT
                           AΡ
                                  AΗ
                                       AFDP
                                              GTEP
                                                       TIT
                                                              TAT
                                                                    TEY
                                                                           CDP
                                                                                    CO
                                                                                         NOX
                6.8594
                       1007.9
                               96.799
                                      3.5000
                                             19.663 1059.2
                                                           550.00 114.70
                                                                         10.605
                                                                                3.1547
                                                                                        82.722
                6.7850 1008.4
                                            19.728 1059.3 550.00 114.72 10.598
                               97.118 3.4998
                                                                                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
                7.0569
                       1009.2
                               95.249
                                     3.4805
                                             19.792
                                                    1059.6
                                                           549.99
                                                                  114.72
                                                                         10.606
                                                                                 3.1923
                                                                                        82.670
                7.3978 1009.7
                               95.150 3.4976
                                             19.765
                                                    1059.7
                                                          549.98 114.72
                                                                         10.612 3.2484
                                                                                        82.311
                                   ...
                                      3.5421
                9.0301
                        1005.6
                               98.460
                                                    1049.7
                                                           546.21
                                                                          10.400
                                                                                4.5186
          15034
                                             19.164
                                                                   111.61
                                                                                        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
          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
In [4]: data.isna().sum()
Out[4]:
         ΑT
                  0
         AP
                  0
         AΗ
                  0
         AFDP
                  0
         GTEP
                  0
         TIT
                  0
         TAT
                  0
         TEY
                  0
         CDP
                  0
         CO
                  0
         NOX
                  0
         dtype: int64
```

In [5]: 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]: data.describe().T

Out[6]:

	count	mean	std	min	25%	50%	75%	max
AT	15039.0	17.764381	7.574323	0.522300	11.408000	18.1860	23.8625	34.9290
AP	15039.0	1013.199240	6.410760	985.850000	1008.900000	1012.8000	1016.9000	1034.2000
АН	15039.0	79.124174	13.793439	30.344000	69.750000	82.2660	90.0435	100.2000
AFDP	15039.0	4.200294	0.760197	2.087400	3.723900	4.1862	4.5509	7.6106
GTEP	15039.0	25.419061	4.173916	17.878000	23.294000	25.0820	27.1840	37.4020
TIT	15039.0	1083.798770	16.527806	1000.800000	1079.600000	1088.7000	1096.0000	1100.8000
TAT	15039.0	545.396183	7.866803	512.450000	542.170000	549.8900	550.0600	550.6100
TEY	15039.0	134.188464	15.829717	100.170000	127.985000	133.7800	140.8950	174.6100
CDP	15039.0	12.102353	1.103196	9.904400	11.622000	12.0250	12.5780	15.0810
СО	15039.0	1.972499	2.222206	0.000388	0.858055	1.3902	2.1604	44.1030
NOX	15039.0	68.190934	10.470586	27.765000	61.303500	66.6010	73.9355	119.8900

```
In [7]: data.corr()
```

Out[7]:

	AT	AP	АН	AFDP	GTEP	TIT	TAT	TEY	(
AT	1.000000	-0.412953	-0.549432	-0.099333	-0.049103	0.093067	0.338569	-0.207495	-0.100
AP	-0.412953	1.000000	0.042573	0.040318	0.078575	0.029650	-0.223479	0.146939	0.131
АН	-0.549432	0.042573	1.000000	-0.119249	-0.202784	-0.247781	0.010859	-0.110272	-0.182
AFDP	-0.099333	0.040318	-0.119249	1.000000	0.744251	0.627254	-0.571541	0.717995	0.727
GTEP	-0.049103	0.078575	-0.202784	0.744251	1.000000	0.874526	-0.756884	0.977042	0.993
TIT	0.093067	0.029650	-0.247781	0.627254	0.874526	1.000000	-0.357320	0.891587	0.887
TAT	0.338569	-0.223479	0.010859	-0.571541	-0.756884	-0.357320	1.000000	-0.720356	-0.744
TEY	-0.207495	0.146939	-0.110272	0.717995	0.977042	0.891587	-0.720356	1.000000	0.988
CDP	-0.100705	0.131198	-0.182010	0.727152	0.993784	0.887238	-0.744740	0.988473	1.000
СО	-0.088588	0.041614	0.165505	-0.334207	-0.508259	-0.688272	0.063404	-0.541751	-0.520
NOX	-0.600006	0.256744	0.143061	-0.037299	-0.208496	-0.231636	0.009888	-0.102631	-0.169

In [8]: # Changing position of target column 'TEY'

Target = data['TEY']
#Drop the existing column

data.drop(labels=['TEY'], axis=1,inplace = True)

data.insert(0, 'Y', Target)

data = data.rename({'Y':'TEY'}, axis = 1)

data.head(10)

Out[8]:

	TEY	AT	AP	AH	AFDP	GTEP	TIT	TAT	CDP	co	NOX
0	114.70	6.8594	1007.9	96.799	3.5000	19.663	1059.2	550.00	10.605	3.1547	82.722
1	114.72	6.7850	1008.4	97.118	3.4998	19.728	1059.3	550.00	10.598	3.2363	82.776
2	114.71	6.8977	1008.8	95.939	3.4824	19.779	1059.4	549.87	10.601	3.2012	82.468
3	114.72	7.0569	1009.2	95.249	3.4805	19.792	1059.6	549.99	10.606	3.1923	82.670
4	114.72	7.3978	1009.7	95.150	3.4976	19.765	1059.7	549.98	10.612	3.2484	82.311
5	114.72	7.6998	1010.7	92.708	3.5236	19.683	1059.8	549.97	10.626	3.4467	82.409
6	114.71	7.7901	1011.6	91.983	3.5298	19.659	1060.0	549.87	10.644	3.4874	82.440
7	114.71	7.7139	1012.7	91.348	3.5088	19.673	1059.8	549.92	10.656	3.6043	83.010
8	114.72	7.7975	1013.8	90.196	3.5141	19.634	1060.1	550.09	10.644	3.3943	82.284
9	131.70	8.0820	1015.0	88.597	4.0612	23.406	1083.0	550.21	11.679	1.9081	82.782

[n [9]:	data.c	orr()								
Out[9]:		TEY	AT	AP	АН	AFDP	GTEP	TIT	TAT	(
	TEY	1.000000	-0.207495	0.146939	-0.110272	0.717995	0.977042	0.891587	-0.720356	0.988
	AT	-0.207495	1.000000	-0.412953	-0.549432	-0.099333	-0.049103	0.093067	0.338569	-0.100
	AP	0.146939	-0.412953	1.000000	0.042573	0.040318	0.078575	0.029650	-0.223479	0.131
	АН	-0.110272	-0.549432	0.042573	1.000000	-0.119249	-0.202784	-0.247781	0.010859	-0.182
	AFDP	0.717995	-0.099333	0.040318	-0.119249	1.000000	0.744251	0.627254	-0.571541	0.727
	GTEP	0.977042	-0.049103	0.078575	-0.202784	0.744251	1.000000	0.874526	-0.756884	0.993
	TIT	0.891587	0.093067	0.029650	-0.247781	0.627254	0.874526	1.000000	-0.357320	0.887
	TAT	-0.720356	0.338569	-0.223479	0.010859	-0.571541	-0.756884	-0.357320	1.000000	-0.744
	CDP	0.988473	-0.100705	0.131198	-0.182010	0.727152	0.993784	0.887238	-0.744740	1.000
	со	-0.541751	-0.088588	0.041614	0.165505	-0.334207	-0.508259	-0.688272	0.063404	-0.520
	NOX	-0.102631	-0.600006	0.256744	0.143061	-0.037299	-0.208496	-0.231636	0.009888	-0.169
	4									•

feature selection by using mutual information Feature Selection

```
In [10]: from sklearn.model_selection import train_test_split
    from sklearn.feature_selection import SelectKBest
    from sklearn.feature_selection import mutual_info_regression
In [11]: x = data.iloc[:,1:]
y = data.iloc[:, 0 ]
```

						`					
In [12]:	x										
Out[12]:		AT	AP	АН	AFDP	GTEP	TIT	TAT	CDP	со	NOX
	0	6.8594	1007.9	96.799	3.5000	19.663	1059.2	550.00	10.605	3.1547	82.722
	1	6.7850	1008.4	97.118	3.4998	19.728	1059.3	550.00	10.598	3.2363	82.776
	2	6.8977	1008.8	95.939	3.4824	19.779	1059.4	549.87	10.601	3.2012	82.468
	3	7.0569	1009.2	95.249	3.4805	19.792	1059.6	549.99	10.606	3.1923	82.670
	4	7.3978	1009.7	95.150	3.4976	19.765	1059.7	549.98	10.612	3.2484	82.311
	15034	9.0301	1005.6	98.460	3.5421	19.164	1049.7	546.21	10.400	4.5186	79.559
	15035	7.8879	1005.9	99.093	3.5059	19.414	1046.3	543.22	10.433	4.8470	79.917
	15036	7.2647	1006.3	99.496	3.4770	19.530	1037.7	537.32	10.483	7.9632	90.912
	15037	7.0060	1006.8	99.008	3.4486	19.377	1043.2	541.24	10.533	6.2494	93.227
	15038	6.9279	1007.2	97.533	3.4275	19.306	1049.9	545.85	10.583	4.9816	92.498
	15039 ı	rows × 1	0 colum	ıns							
n [13]:	у										
ut[13]:	0	114	.70								
	1	114	.72								
	2	114	.71								
	3	114	.72								
	4	114	.72								
		• • •	•								
	15034	111	.61								
	15035	111	.78								
	15036	110	.19								
	15037	110	.74								

```
In [17]: #Feature selection
def select_features(x_train,y_train,x_test):
    #configure to select all features
    fs = SelectKBest(score_func = mutual_info_regression,k = 'all')
    #Learn relationship from training data
    fs.fit(x_train,y_train)
    #transform train input data
    x_train_fs = fs.transform(x_train)
    #transfer test input data
    x_test_fs = fs.transform(x_test)
    return x_train_fs,x_test_fs, fs
```

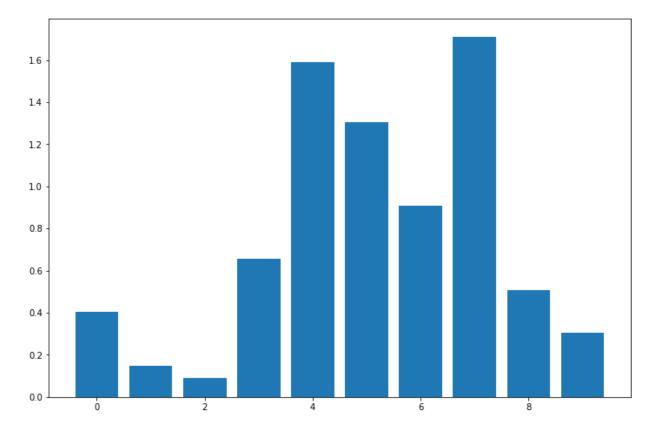
```
In [18]: # split into train and test sets
    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.33, random_
    # feature selection
    x_train_fs, x_test_fs, fs = select_features(x_train, y_train, x_test)
```

15038

111.58

Name: TEY, Length: 15039, dtype: float64

Feature 0: 0.402863
Feature 1: 0.147218
Feature 2: 0.091173
Feature 3: 0.656688
Feature 4: 1.590872
Feature 5: 1.306241
Feature 6: 0.909771
Feature 7: 1.711018
Feature 8: 0.507201
Feature 9: 0.303863



As per above features selection method, we will select only features with good score to build our model

```
In [21]: x = data.drop(['TEY','AT','AP','AH', 'CO','NOX'], axis= 1 )
y = data.iloc[:,0]
```

```
In [22]: x
```

```
Out[22]:
                   AFDP
                          GTEP
                                   TIT
                                         TAT
                                                CDP
               0 3.5000 19.663 1059.2 550.00 10.605
               1 3.4998 19.728 1059.3 550.00 10.598
               2 3.4824 19.779 1059.4 549.87
                                              10.601
                 3.4805 19.792 1059.6 549.99
                  3.4976 19.765 1059.7 549.98
                                              10.612
           15034 3.5421 19.164 1049.7 546.21
                                              10.400
           15035 3.5059 19.414 1046.3 543.22 10.433
           15036 3.4770 19.530 1037.7 537.32
           15037 3.4486 19.377 1043.2 541.24
                                              10.533
           15038 3.4275 19.306 1049.9 545.85 10.583
```

15039 rows × 5 columns

```
In [23]: y
Out[23]: 0
                   114.70
          1
                   114.72
          2
                   114.71
          3
                   114.72
          4
                   114.72
                    . . .
          15034
                   111.61
          15035
                   111.78
                   110.19
          15036
          15037
                   110.74
          15038
                   111.58
          Name: TEY, Length: 15039, dtype: float64
In [24]: from sklearn.model selection import train test split
          x train,x test,y train,y test = train test split(x,y, test size=0.20)
```

Arificial neural network model - backpropagation

```
In [25]: from keras.models import Sequential
    from keras.layers import Dense

In [26]: #Create model
    model = Sequential()
    model.add(Dense(10, input_dim=5,activation='relu'))
    model.add(Dense(6, activation= 'relu'))
    model.add(Dense(1, activation='sigmoid'))
```

```
In [27]: #Compile model
        model.compile(loss='mean squared error', optimizer = 'adam', metrics=['mse'])
In [28]: #fit the model
       history = model.fit(x, y, validation split=0.33,epochs=100, batch size=40)
        252/252 [============= ] - 5s 7ms/step - loss: 18290.0293 - m
        se: 18290.0293 - val_loss: 17380.0664 - val_mse: 17380.0664
        Epoch 2/100
        252/252 [============ ] - 1s 6ms/step - loss: 18290.0254 - m
        se: 18290.0254 - val loss: 17380.0664 - val mse: 17380.0664
        Epoch 3/100
        252/252 [============ ] - 1s 5ms/step - loss: 18290.0293 - m
        se: 18290.0293 - val_loss: 17380.0664 - val_mse: 17380.0664
        Epoch 4/100
        se: 18290.0254 - val_loss: 17380.0664 - val_mse: 17380.0664
        Epoch 5/100
        252/252 [============ ] - 1s 5ms/step - loss: 18290.0195 - m
        se: 18290.0195 - val_loss: 17380.0664 - val_mse: 17380.0664
        Epoch 6/100
        252/252 [========== ] - 1s 5ms/step - loss: 18290.0352 - m
        se: 18290.0352 - val loss: 17380.0664 - val mse: 17380.0664
        252/252 5
                                                             40000 0054
In [29]: # evaluate the model
        scores = model.evaluate(x, y)
        print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
        e: 17989.7305
        mse: 1798973.05%
        Hyper parameter tuning
In [31]: X = data.drop(['TEY', 'AT', 'AP', 'AH', 'CO', 'NOX'], axis= 1)
        Y =data.iloc[:,0]
```

```
In [32]: X
```

Out[32]	:
------	-----	---

AFDP	GTEP	TIT	TAT	CDP
3.5000	19.663	1059.2	550.00	10.605
3.4998	19.728	1059.3	550.00	10.598
3.4824	19.779	1059.4	549.87	10.601
3.4805	19.792	1059.6	549.99	10.606
3.4976	19.765	1059.7	549.98	10.612
3.5421	19.164	1049.7	546.21	10.400
3.5059	19.414	1046.3	543.22	10.433
3.4770	19.530	1037.7	537.32	10.483
3.4486	19.377	1043.2	541.24	10.533
3.4275	19.306	1049.9	545.85	10.583
	3.5000 3.4998 3.4824 3.4805 3.4976 3.5421 3.5059 3.4770 3.4486	3.5000 19.663 3.4998 19.728 3.4824 19.779 3.4805 19.765 3.5421 19.164 3.5059 19.414 3.4770 19.530 3.4486 19.377	3.5000 19.663 1059.2 3.4998 19.728 1059.3 3.4824 19.779 1059.4 3.4805 19.792 1059.6 3.4976 19.765 1059.7 3.5421 19.164 1049.7 3.5059 19.414 1046.3 3.4770 19.530 1037.7 3.4486 19.377 1043.2	3.5000 19.663 1059.2 550.00 3.4998 19.728 1059.3 550.00 3.4824 19.779 1059.4 549.87 3.4805 19.792 1059.6 549.99 3.4976 19.765 1059.7 549.98 3.5421 19.164 1049.7 546.21 3.5059 19.414 1046.3 543.22 3.4770 19.530 1037.7 537.32 3.4486 19.377 1043.2 541.24

15039 rows × 5 columns

```
In [33]: Y
```

```
Out[33]: 0
```

```
114.70
114.72
```

- 2 114.71
- 3 114.72
- 114.72 . . .
- 15034 111.61 111.78 15035
- 15036 110.19
- 110.74 15037
- 15038 111.58

Name: TEY, Length: 15039, dtype: float64

In [34]: # Standardization

from sklearn.preprocessing import StandardScaler

- a = StandardScaler()
- a.fit(X)

X_standardized = a.transform(X)

In [35]: pd.DataFrame(X_standardized).describe().T

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- ()	ш	тι	1 35	1.
_	u	_		

count	mean	std	min	25%	50%	75%	max
 0 15039.0	3.810001e-16	1.000033	-2.779497	-0.626693	-0.018541	0.461220	4.486233
1 15039.0	1.107344e-16	1.000033	-1.806771	-0.509146	-0.080757	0.422864	2.871006
2 15039.0	-2.324212e-15	1.000033	-5.021933	-0.254051	0.296554	0.738249	1.028678
3 15039.0	1.744899e-15	1.000033	-4.188141	-0.410115	0.571257	0.592868	0.662784
4 15039.0	3.640356e-16	1.000033	-1.992416	-0.435434	-0.070119	0.431168	2.700105

Tuning of all hyperparameters

```
In [42]: from sklearn.model selection import GridSearchCV
         from keras.models import Sequential
         from keras.layers import Dense
         from keras.wrappers.scikit learn import KerasClassifier
         from keras.layers import Dropout
         from tensorflow.keras.optimizers import Adam
         import warnings
         warnings.filterwarnings('ignore')
In [38]: # Splitting data into test and train data
         from sklearn.model selection import train test split
         X train, X test, Y train, Y test = train test split(X,Y,test size=0.3, random state=
In [40]: def create model(learning rate, dropout rate, activation function, init, neuron1, neur
             model = Sequential()
             model.add(Dense(neuron1,input dim = 5,kernel initializer = init,activation =
             model.add(Dropout(dropout rate))
             model.add(Dense(neuron2,input dim = neuron1,kernel initializer = init,activat
             model.add(Dropout(dropout rate))
             model.add(Dense(1,activation = 'sigmoid'))
             adam = Adam(lr =learning rate)
             model.compile(loss = 'mean squared error',optimizer = adam,metrics = ['mse'])
             return model
In [43]: #Create the model
         model= KerasClassifier(build fn= create model, verbose =0)
In [45]: #Define the grid search parameters
         batch_size = [10,20,40]
         epochs = [10,50,100]
         learning rate = [0.001, 0.01, 0.1]
         dropout rate = [0.0, 0.1, 0.2]
         activation_function = ['softmax','relu', 'tanh','linear']
         init = ['uniform','normal','zero']
         neuron1 = [4,8,16]
         neuron2 = [2,4,8]
In [46]: # Make a dictionary of the grid search parameters
         param grids = dict(batch size = batch size,epochs = epochs,learning rate = learni
                             activation function = activation function, init = init, neuron1
```

```
In [47]: # Build and fit the GridSearchCV
         grid = GridSearchCV(estimator = model,param grid = param grids,verbose = 10, scor
         grid result = grid.fit(X, Y)
         # Summarize the results
         print('Best : {}, using {}'.format(grid result.best score ,grid result.best param
         Fitting 5 folds for each of 8748 candidates, totalling 43740 fits
         [CV 1/5; 1/8748] START activation function=softmax, batch size=10, dropout ra
         te=0.0, epochs=10, init=uniform, learning rate=0.001, neuron1=4, neuron2=2
         [CV 1/5; 1/8748] END activation_function=softmax, batch_size=10, dropout_rate
         =0.0, epochs=10, init=uniform, learning rate=0.001, neuron1=4, neuron2=2; tot
         al time= 37.7s
         [CV 2/5; 1/8748] START activation function=softmax, batch size=10, dropout ra
         te=0.0, epochs=10, init=uniform, learning rate=0.001, neuron1=4, neuron2=2
         [CV 2/5; 1/8748] END activation function=softmax, batch size=10, dropout rate
         =0.0, epochs=10, init=uniform, learning rate=0.001, neuron1=4, neuron2=2; tot
         al time= 36.5s
         [CV 3/5; 1/8748] START activation function=softmax, batch size=10, dropout ra
         te=0.0, epochs=10, init=uniform, learning rate=0.001, neuron1=4, neuron2=2
         [CV 3/5; 1/8748] END activation function=softmax, batch size=10, dropout rate
         =0.0, epochs=10, init=uniform, learning rate=0.001, neuron1=4, neuron2=2; tot
         al time= 35.9s
         [CV 4/5; 1/8748] START activation_function=softmax, batch_size=10, dropout_ra
         te=0.0, epochs=10, init=uniform, learning rate=0.001, neuron1=4, neuron2=2
```

[CV 4/5; 1/8748] END activation_function=softmax, batch_size=10, dropout_rate