Tushar Naik

Project Title: ANN Mining process flotation plant database

```
In [1]:
```

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

In [2]:

```
df = pd.read_csv("D:\ML Lecture\ML Datasets\MiningProcess_Flotation_Plant_Database.csv")
df.head()
```

Out[2]:

	date	% Iron Feed	% Silica Feed	Starch Flow	Amina Flow	Ore Pulp Flow	Ore Pulp pH	Ore Pulp Density	Flotation Column 01 Air Flow	Flotation Column 02 Air Flow	 Flotation Column 07 Air Flow	Flotation Column 01 Level		•
0	2017- 03-10 01:00:00	55,2	16,98	3019,53	557,434	395,713	10,0664	1,74	249,214	253,235	 250,884	457,396	432,962	,
1	2017- 03-10 01:00:00	55,2	16,98	3024,41	563,965	397,383	10,0672	1,74	249,719	250,532	 248,994	451,891	429,56	,
2	2017- 03-10 01:00:00	55,2	16,98	3043,46	568,054	399,668	10,068	1,74	249,741	247,874	 248,071	451,24	468,927	
3	2017- 03-10 01:00:00	55,2	16,98	3047,36	568,665	397,939	10,0689	1,74	249,917	254,487	 251,147	452,441	458,165	,
4	2017- 03-10 01:00:00	55,2	16,98	3033,69	558,167	400,254	10,0697	1,74	250,203	252,136	 248,928	452,441	452,9	,

5 rows × 24 columns

In [3]:

```
# replacing ',' with '.'
def XYZ(x):
    return x.str.replace(",",".")
```

In [4]:

```
# applying changes
df = df.apply(XYZ)
```

In [5]:

```
df.info()
<class 'pandas.core.frame.DataFrame'>
```

```
o TTOIL LEEM
                                 INITON HOW HATT ONDECE
    % Silica Feed
                                 737453 non-null object
                                 737453 non-null object
 3
    Starch Flow
                                 737453 non-null object
    Amina Flow
 5
   Ore Pulp Flow
                                 737453 non-null object
   Ore Pulp pH
                                 737453 non-null object
 7
   Ore Pulp Density
                                 737453 non-null object
8 Flotation Column 01 Air Flow 737453 non-null object
 9 Flotation Column 02 Air Flow 737453 non-null object
10 Flotation Column 03 Air Flow 737453 non-null object
11 Flotation Column 04 Air Flow 737453 non-null object
12 Flotation Column 05 Air Flow 737453 non-null object
13 Flotation Column 06 Air Flow 737453 non-null object
14 Flotation Column 07 Air Flow 737453 non-null object
15 Flotation Column 01 Level
                                 737453 non-null object
16 Flotation Column 02 Level
                                 737453 non-null object
17 Flotation Column 03 Level
                                 737453 non-null object
18 Flotation Column 04 Level
                                 737453 non-null object
19 Flotation Column 05 Level
                                 737453 non-null object
 20 Flotation Column 06 Level
                                 737453 non-null object
 21 Flotation Column 07 Level
                                 737453 non-null object
22 % Iron Concentrate
                                 737453 non-null object
23 % Silica Concentrate
                                 737453 non-null object
dtypes: object(24)
memory usage: 135.0+ MB
```

In [6]:

```
# droping unwanted columns
df.drop("date", axis=1, inplace=True)
```

In [7]:

```
# changing datatype
df = df.astype(float)
```

In [8]:

df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 737453 entries, 0 to 737452

Data columns (total 23 columns):

#	Column	Non-Nu	Dtype							
0	% Iron Feed	737453	non-null	float64						
1	% Silica Feed	737453	non-null	float64						
2	Starch Flow	737453	non-null	float64						
3	Amina Flow	737453	non-null	float64						
4	Ore Pulp Flow	737453	non-null	float64						
5	Ore Pulp pH	737453	non-null	float64						
6	Ore Pulp Density	737453	non-null	float64						
7	Flotation Column 01 Ai	r Flow	737453	non-null	float64					
8	Flotation Column 02 Ai	r Flow	737453	non-null	float64					
9	Flotation Column 03 Ai	r Flow	737453	non-null	float64					
10	Flotation Column 04 Ai	r Flow	737453	non-null	float64					
11	Flotation Column 05 Ai	r Flow	737453	non-null	float64					
12	Flotation Column 06 Ai	r Flow	737453	non-null	float64					
13	Flotation Column 07 Ai	r Flow	737453	non-null	float64					
14	Flotation Column 01 Le	vel	737453	non-null	float64					
15	Flotation Column 02 Le	vel	737453	non-null	float64					
16	Flotation Column 03 Le	vel	737453	non-null	float64					
17	Flotation Column 04 Le	vel	737453	non-null	float64					
18	Flotation Column 05 Le	vel	737453	non-null	float64					
19	Flotation Column 06 Le	vel	737453	non-null	float64					
20	Flotation Column 07 Le	737453	non-null	float64						
21	% Iron Concentrate	737453	non-null	float64						
22	% Silica Concentrate	737453	non-null	float64						
dtypes: float64(23)										

dtypes: float64(23) memory usage: 129.4 MB df

Out[9]:

	% Iron Feed	% Silica Feed	Starch Flow	Amina Flow	Ore Pulp Flow	Ore Pulp pH	Ore Pulp Density	Flotation Column 01 Air Flow	Flotation Column 02 Air Flow	Flotation Column 03 Air Flow	 Flotation Column 07 Air Flow	Flotation Column 01 Level	Flota Col 02 I
0	55.20	16.98	3019.53	557.434	395.713	10.06640	1.74000	249.214	253.235	250.576	 250.884	457.396	432
1	55.20	16.98	3024.41	563.965	397.383	10.06720	1.74000	249.719	250.532	250.862	 248.994	451.891	429
2	55.20	16.98	3043.46	568.054	399.668	10.06800	1.74000	249.741	247.874	250.313	 248.071	451.240	468
3	55.20	16.98	3047.36	568.665	397.939	10.06890	1.74000	249.917	254.487	250.049	 251.147	452.441	458
4	55.20	16.98	3033.69	558.167	400.254	10.06970	1.74000	250.203	252.136	249.895	 248.928	452.441	452
•••											 		
737448	49.75	23.20	2710.94	441.052	386.570	9.62129	1.65365	302.344	298.786	299.163	 313.695	392.160	430
737449	49.75	23.20	2692.01	473.436	384.939	9.62063	1.65352	303.013	301.879	299.487	 236.700	401.505	404
737450	49.75	23.20	2692.20	500.488	383.496	9.61874	1.65338	303.662	307.397	299.487	 225.879	408.899	399
737451	49.75	23.20	1164.12	491.548	384.976	9.61686	1.65324	302.550	301.959	298.045	 308.115	405.107	466
737452	49.75	23.20	1164.12	468.019	384.801	9.61497	1.65310	300.355	292.865	298.625	 308.115	413.754	514

737453 rows × 23 columns

1

In [10]:

```
# Preprocessing the data X split, Y split
from sklearn.preprocessing import StandardScaler
SS = StandardScaler()
X = df.iloc[:,:-1]
X = SS.fit_transform(X)
X
```

Out[10]:

```
array([[-0.21225167, 0.34202086, 0.12375664, ..., 0.18282424, 1.20533681, 1.66266665], [-0.21225167, 0.34202086, 0.12777243, ..., 0.17783883, 0.90767427, 1.66266665], [-0.21225167, 0.34202086, 0.14344883, ..., 0.19902684, 0.44227984, 1.66266665], ..., [-1.26891589, 1.25572783, -0.14560578, ..., -1.04500062, 0.1426383, -0.69733357], [-1.26891589, 1.25572783, -1.40307479, ..., -0.99148533, 0.15248617, -0.69733357], [-1.26891589, 1.25572783, -1.40307479, ..., -0.61858089, 0.23748886, -0.69733357]])
```

In [11]:

```
Y = df.iloc[:,-1]
Y
```

Out[11]:

```
1.31
          1.31
1
2
          1.31
3
          1.31
          1.31
737448
           1.71
737449
          1.71
737450
          1.71
727151
          1 71
```

```
1. / 1
131431
737452
      1.71
Name: % Silica Concentrate, Length: 737453, dtype: float64
In [12]:
# Spliting data and training the data
from sklearn.model selection import train test split
X train, X test, Y train, Y test = train test split(X, Y, train size=0.3, random state=1)
In [13]:
#!pip install tensorflow
In [14]:
import tensorflow as tf
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, Dropout
In [15]:
# Implementing the early stop method
from tensorflow.keras.callbacks import EarlyStopping
early stop=EarlyStopping(monitor="val loss", mode="min", verbose=1, patience=20)
In [16]:
# step1 :- initialize the Model
ann = Sequential()
# step2 :- Add Layers into model
ann.add(Dense(units = 20, activation = "relu") ) # HL add
ann.add(Dropout(0.06))
ann.add( Dense(units = 20, activation = "relu") )
ann.add(Dropout(0.04))
ann.add( Dense(units = 1) ) #op layer
# step3 :- Establihing connection
ann.compile(optimizer='adam', loss = 'mse')
# step4 :- Fit the model
ann.fit(X train,Y train,epochs=600,validation data=(X test,Y test),verbose=1,batch size=
128, callbacks=[early_stop])
# step5 :- Predict the model
#Y pred = ann.predict(X test)
Epoch 1/600
Epoch 2/600
Epoch 3/600
Epoch 4/600
Epoch 5/600
Epoch 6/600
Epoch 7/600
15
```

```
Epoch 8/600
Epoch 9/600
Epoch 10/600
Epoch 11/600
Epoch 12/600
Epoch 13/600
Epoch 14/600
Epoch 15/600
Epoch 16/600
Epoch 17/600
Epoch 18/600
Epoch 19/600
Epoch 20/600
Epoch 21/600
Epoch 22/600
Epoch 23/600
Epoch 24/600
Epoch 25/600
Epoch 26/600
Epoch 27/600
Epoch 28/600
Epoch 29/600
Epoch 30/600
Epoch 31/600
```

```
Epoch 32/600
Epoch 33/600
Epoch 34/600
Epoch 35/600
Epoch 36/600
1729/1729 [==========
     =======] - 7s 4ms/step - loss: 0.2692 - val loss: 0.238
Epoch 37/600
Epoch 38/600
7.5
Epoch 39/600
Epoch 40/600
Epoch 41/600
Epoch 42/600
Epoch 43/600
Epoch 44/600
Epoch 45/600
Epoch 46/600
Epoch 47/600
Epoch 48/600
Epoch 49/600
Epoch 50/600
Epoch 51/600
Epoch 52/600
Epoch 53/600
Epoch 54/600
Epoch 55/600
```

```
Epoch 56/600
Epoch 57/600
Epoch 58/600
Epoch 59/600
Epoch 60/600
1729/1729 [==========
    ========] - 9s 5ms/step - loss: 0.2641 - val loss: 0.233
Epoch 61/600
Epoch 62/600
Epoch 63/600
Epoch 64/600
Epoch 65/600
Epoch 66/600
Epoch 67/600
Epoch 68/600
Epoch 69/600
Epoch 70/600
Epoch 71/600
Epoch 72/600
Epoch 73/600
Epoch 74/600
98
Epoch 75/600
Epoch 76/600
Epoch 77/600
36
Epoch 78/600
Epoch 79/600
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Epoch 80/600
Epoch 81/600
Epoch 82/600
Epoch 83/600
Epoch 84/600
Epoch 85/600
Epoch 86/600
Epoch 87/600
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Epoch 89/600
Epoch 90/600
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Epoch 92/600
Epoch 93/600
Epoch 94/600
Epoch 95/600
Epoch 96/600
Epoch 97/600
84
Epoch 98/600
96
Epoch 99/600
Epoch 100/600
Epoch 101/600
Epoch 102/600
Epoch 103/600
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Epoch 104/600
Epoch 105/600
Epoch 106/600
Epoch 107/600
Epoch 108/600
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Epoch 110/600
Epoch 111/600
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Epoch 116/600
Epoch 117/600
Epoch 118/600
Epoch 119/600
80
Epoch 120/600
Epoch 121/600
Epoch 122/600
Epoch 123/600
Epoch 124/600
Epoch 125/600
Epoch 126/600
Epoch 127/600
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```
Epoch 128/600
Epoch 129/600
Epoch 130/600
Epoch 131/600
Epoch 132/600
Epoch 133/600
Epoch 134/600
Epoch 135/600
Epoch 136/600
70
Epoch 137/600
Epoch 138/600
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Epoch 141/600
Epoch 142/600
Epoch 143/600
Epoch 144/600
Epoch 145/600
Epoch 146/600
Epoch 147/600
Epoch 148/600
Epoch 149/600
Epoch 150/600
Epoch 151/600
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Epoch 152/600
Epoch 153/600
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Epoch 174/600
Epoch 175/600
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Epoch 176/600
Epoch 177/600
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Epoch 193/600
Epoch 194/600
Epoch 195/600
Epoch 196/600
Epoch 197/600
Epoch 198/600
Epoch 199/600
```

```
Epoch 200/600
Epoch 201/600
Epoch 202/600
Epoch 203/600
Epoch 204/600
1729/1729 [==========
    ========] - 6s 4ms/step - loss: 0.2566 - val loss: 0.224
Epoch 205/600
Epoch 206/600
Epoch 207/600
Epoch 208/600
Epoch 209/600
Epoch 210/600
Epoch 211/600
Epoch 212/600
Epoch 213/600
Epoch 214/600
Epoch 215/600
Epoch 216/600
Epoch 217/600
Epoch 218/600
Epoch 219/600
Epoch 220/600
Epoch 221/600
Epoch 222/600
Epoch 223/600
```

```
Epoch 224/600
Epoch 225/600
Epoch 226/600
Epoch 227/600
Epoch 228/600
1729/1729 [=====
      ========] - 7s 4ms/step - loss: 0.2564 - val loss: 0.223
Epoch 229/600
Epoch 230/600
Epoch 231/600
Epoch 232/600
Epoch 233/600
Epoch 234/600
Epoch 235/600
Epoch 235: early stopping
Out[16]:
```

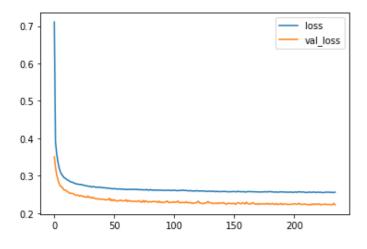
<keras.callbacks.History at 0x1e2144cb700>

In [17]:

```
# Plotting the Graph
lossdf=pd.DataFrame(ann.history.history)
lossdf.plot()
```

Out[17]:

<AxesSubplot: >



In [18]:

```
# step5 :- Predict the model
Y_pred = ann.predict(X_test)
```

```
16132/16132 [=========== ] - 16s 989us/step
In [19]:
# R2 Score of the dataset
from sklearn.metrics import r2 score
print(f"R2 --> {r2 score(Y test, Y pred)}")
R2 --> 0.8245288584517543
In [20]:
from sklearn.metrics import mean absolute error, mean squared error
print(f"MAE ---> {mean_absolute_error(Y_test,Y_pred)}")
print(f"MSE ---> {mean_squared_error(Y_test,Y_pred)}")
print(f"RMSE --> {np.sqrt(mean squared error(Y test,Y pred))}")
MAE ---> 0.3486876390334765
MSE ---> 0.22257738618837422
RMSE --> 0.4717810786671867
In [ ]:
In [ ]:
```