```
In [1]: import numpy as np
   import pandas as pd
   import seaborn as sns
   import matplotlib.pyplot as plt
   from sklearn import metrics
   from sklearn.metrics import mean_squared_error, mean_absolute_error,accuracy_scor
   from math import sqrt
```

In [2]: dataset = pd.read\_csv("Data Mill Original3 200.csv")
 dataset

#### Out[2]:

	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	Tool life measured during process (min)
0	100	22	0.2	264
1	100	98	0.4	27
2	100	132	0.6	23
3	100	200	0.8	18
4	100	360	1.0	12
194	1560	360	1.0	44
195	1600	26	0.2	92
196	1600	95	0.4	98
197	1600	136	0.6	99
198	1600	200	1.0	45

199 rows × 4 columns

```
In [3]: X = dataset.drop('Tool life measured during process (min)', axis=1).values
y= dataset['Tool life measured during process (min)']
```

```
In [4]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.1, randor
```

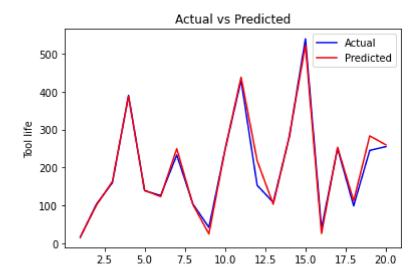
```
In [5]: y_test
Out[5]: 18
                 16
        169
                103
        106
                160
        92
                390
        176
                139
        183
                126
        5
                233
        139
                104
        12
                42
        160
                246
        61
                430
        124
                153
        164
                108
        145
                281
                539
        80
        7
                40
        33
                250
        129
                 99
        37
                245
        74
                255
        Name: Tool life measured during process (min), dtype: int64
In [6]: from sklearn.preprocessing import StandardScaler
        scaler = StandardScaler()
        X_train = scaler.fit_transform(X_train)
        X_test = scaler.transform(X_test)
```

```
In [7]:
        from xgboost.sklearn import XGBRegressor
        eval_set = [(X_train, y_train), (X_test, y_test)]
        eval_metric = ['rmse']
        xg = XGBRegressor(n estimators=1391,eta=0.04,max depth=6)
        %time xg.fit(X_train, y_train, eval_metric=eval_metric, eval_set=eval_set, verbos
        y_pred1 = xg.predict(X_test)
        [0]
                 validation 0-rmse:264.04538
                                                  validation 1-rmse:229.00987
        [1]
                                                  validation_1-rmse:220.08131
                 validation_0-rmse:254.24817
        [2]
                 validation_0-rmse:244.83873
                                                 validation_1-rmse:211.50291
        [3]
                 validation_0-rmse:235.80333
                                                  validation 1-rmse:203.27580
                 validation_0-rmse:227.12620
                                                  validation_1-rmse:195.35924
        [4]
        [5]
                 validation_0-rmse:218.79317
                                                 validation_1-rmse:188.10115
        [6]
                 validation_0-rmse:210.78842
                                                  validation_1-rmse:180.78902
        [7]
                 validation 0-rmse:203.10429
                                                 validation 1-rmse:173.76848
                 validation_0-rmse:195.72650
                                                  validation_1-rmse:167.33556
        [8]
                                                  validation 1-rmse:160.86003
        [9]
                 validation 0-rmse:188.64305
        [10]
                 validation_0-rmse:181.84598
                                                  validation_1-rmse:154.64584
                 validation 0-rmse:175.32120
                                                 validation 1-rmse:148.95267
        [11]
        [12]
                 validation 0-rmse:168.98320
                                                  validation 1-rmse:143.19276
                                                  validation 1-rmse:137.64250
        [13]
                 validation 0-rmse:162.89395
        [14]
                 validation_0-rmse:157.03481
                                                 validation_1-rmse:132.31740
        [15]
                 validation 0-rmse:151.41249
                                                 validation 1-rmse:127.15165
        [16]
                 validation_0-rmse:146.07213
                                                 validation_1-rmse:122.37206
        [17]
                 validation_0-rmse:140.85823
                                                 validation_1-rmse:117.56606
        [18]
                 validation 0-rmse:135.85883
                                                  validation 1-rmse:112.98945
In [8]: |train_list_acc = []
        test list acc = []
        print("Training Accuracy :", xg.score(X_train, y_train))
In [9]:
        print("Testing Accuracy :", xg.score(X_test, y_test))
        train list acc.append(xg.score(X train, y train))
        test_list_acc.append(xg.score(X_test, y_test))
```

Training Accuracy: 0.999999997088664
Testing Accuracy: 0.9801597248618984

```
In [10]: c = [i for i in range(1,len(y_test)+1,1)]
    plt.plot(c, y_test,color = 'Blue',label='Actual')
    plt.plot(c, y_pred1,color = 'red',label='Predicted')
    plt.legend()
    plt.title("Actual vs Predicted")
    plt.ylabel("Tool life")
```

Out[10]: Text(0, 0.5, 'Tool life')



```
In [11]: scores= metrics.mean_squared_error(y_test,y_pred1)
In [12]: scores
Out[12]: 353.0268940553662
In [13]: y_pred1
Out[13]: array([ 16.811922, 100.18857 , 163.22873 , 387.62717 , 139.55034 , 123.099724, 249.65125 , 102.6492 , 24.900478, 246.45819 , 438.07037 , 217.92616 , 102.97632 , 282.94662 , 521.8817 , 26.118086, 253.1232 , 112.07201 , 283.15424 , 259.88138 ], dtype=float32)
```

In [14]: pd.DataFrame(y\_pred1)

### Out[14]:

- 16.811922
- 100.188568
- 163.228729
- 387.627167
- 4 139.550339
- 123.099724
- 249.651245
- 102.649200
- 8 24.900478
- 246.458191
- 438.070374
- 217.926163
- 102.976318
- 282.946625
- 521.881714
- 26.118086
- 253.123199
- 112.072006
- 283.154236
- 259.881378

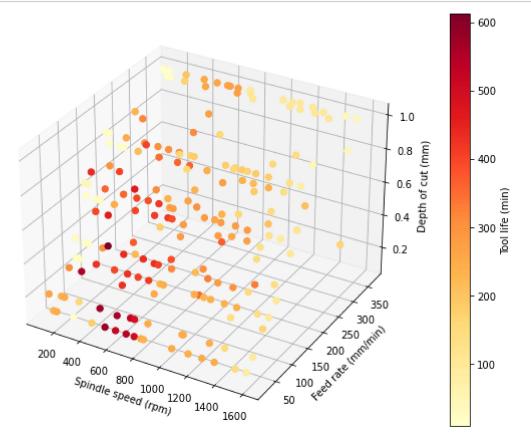
In [15]: pd.DataFrame(y\_test)

## Out[15]:

# Tool life measured during process (min)

	Tool life measured during process (min)
18	16
169	103
106	160
92	390
176	139
183	126
5	233
139	104
12	42
160	246
61	430
124	153
164	108
145	281
80	539
7	40
33	250
129	99
37	245
74	255

```
In [16]: from mpl_toolkits.mplot3d import Axes3D
    plt.rcParams["figure.figsize"] = [12.00, 6]
    plt.rcParams["figure.autolayout"] = True
    fig = plt.figure()
    ax = fig.add_subplot(111, projection='3d')
    x = dataset['Spindle speed (rpm)']
    y = dataset['Feed rate (mm/min)']
    z = dataset['Depth of cut (mm)']
    c = dataset['Tool life measured during process (min)']
    ax.set_xlabel('Spindle speed (rpm)')
    ax.set_ylabel('Feed rate (mm/min)')
    ax.set_zlabel('Depth of cut (mm)')
    img = ax.scatter(x, y, z, c=c,s=40, cmap='YlOrRd', alpha=1)
    fig.colorbar(img).set_label('Tool life (min)')
    plt.show()
```

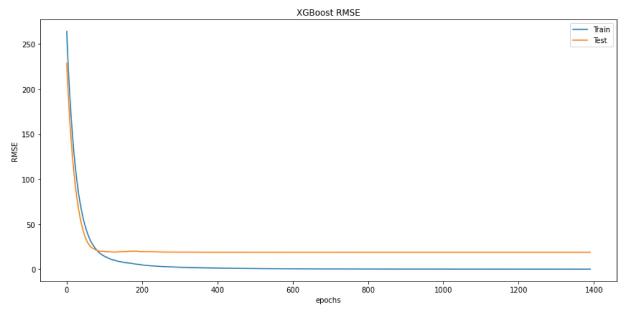


```
In [17]: import pandas as pd
         import plotly
         import plotly.graph_objs as go
         #Set marker properties
         markercolor = dataset['Tool life measured during process (min)']
         #Make Plotly figure
         fig1 = go.Scatter3d(x=dataset['Spindle speed (rpm)'],
                             y=dataset['Feed rate (mm/min)'],
                              z=dataset['Depth of cut (mm)'],
                             marker=dict(color=markercolor,
                                          opacity=1,
                                          reversescale=True,
                                          colorscale='ylgnbu',
                                          size=5),
                              line=dict (width=0.02),
                             mode='markers')
         #Make Plot.ly Layout
         mylayout = go.Layout(scene=dict(xaxis=dict( title="Spindle speed (rpm)"),
                                          yaxis=dict( title="Feed rate (mm/min)"),
                                          zaxis=dict(title="Depth of cut (mm)")),)
         #Plot and save html
         plotly.offline.plot({"data": [fig1],
                               "layout": mylayout},
                               auto_open=True,
                               filename=("4DPlot.html"))
```

#### Out[17]: '4DPlot.html'

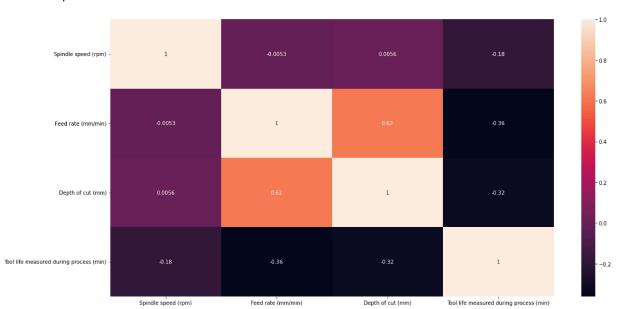
## In [18]: from sklearn.metrics import accuracy\_score

```
In [19]: results = xg.evals_result()
    epochs = len(results['validation_0']['rmse'])
    x_axis = range(0, epochs)
# plot log loss
fig, ax = plt.subplots()
    ax.plot(x_axis, results['validation_0']['rmse'], label='Train')
    ax.plot(x_axis, results['validation_1']['rmse'], label='Test')
    ax.legend()
    plt.ylabel('RMSE')
    plt.xlabel('epochs')
    plt.title('XGBoost RMSE')
    plt.show()
```



```
In [20]: plt.figure(figsize=(18,8))
sns.heatmap(dataset.corr(), annot = True)
```

### Out[20]: <AxesSubplot:>



In [21]: dataset.describe()

#### Out[21]:

	Tool life measured during process (min)	Depth of cut (mm)	Feed rate (mm/min)	Spindle speed (rpm)	
•	199.000000	199.000000	199.000000	199.000000	count
	234.351759	0.599497	157.296482	806.532663	mean
	136.987564	0.311480	111.586935	446.321992	std
	9.000000	0.100000	22.000000	100.000000	min
	136.000000	0.300000	90.000000	437.500000	25%
	239.000000	0.600000	130.000000	765.000000	50%
	308.000000	0.900000	200.000000	1180.000000	75%
	612.000000	1.000000	370.000000	1600.000000	max

## In [22]: dataset.kurt()

Out[22]: Spindle speed (rpm) -1.172023
Feed rate (mm/min) -0.591722
Depth of cut (mm) -1.398414
Tool life measured during process (min) -0.257024
dtype: float64

## In [23]: dataset.kurtosis()

Out[23]: Spindle speed (rpm) -1.172023
Feed rate (mm/min) -0.591722
Depth of cut (mm) -1.398414
Tool life measured during process (min) -0.257024
dtype: float64

#### In [24]: dataset.var()

Out[24]: Spindle speed (rpm) 199203.320897
Feed rate (mm/min) 12451.643977
Depth of cut (mm) 0.097020
Tool life measured during process (min) 18765.592813
dtype: float64

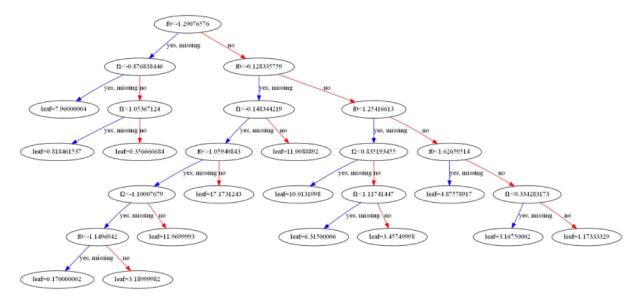
In [25]: dataset.skew()

Out[25]: Spindle speed (rpm) 0.110613
Feed rate (mm/min) 0.716438
Depth of cut (mm) -0.155323
Tool life measured during process (min) 0.358313
dtype: float64

In [26]: from xgboost import plot\_tree

```
In [27]: plot_tree(xg)
```

#### Out[27]: <AxesSubplot:>



#### In [28]:

```
Out[28]: array([[-1.40926603e+00,
                                                     6.73920915e-01],
                                    4.16238798e-01,
                 [ 1.17516596e+00,
                                    1.81859014e+00,
                                                     1.31901099e+00],
                 [ 1.45012163e-03, -2.02981276e-01,
                                                     1.31901099e+00],
                 [-1.56550087e-01, -1.66556566e-01,
                                                     2.88308413e-02],
                 [ 1.44602346e+00, -5.12591313e-01,
                                                     2.88308413e-02],
                 [ 1.51373783e+00, 2.52327602e-01,
                                                     9.96465952e-01],
                 [-1.54469478e+00, -1.18644845e+00, -1.58389434e+00],
                                                     1.31901099e+00],
                 [ 6.56022414e-01, 1.74574072e+00,
                 [-1.48826613e+00, -3.12255407e-01,
                                                     3.51375878e-01],
                 [ 1.08488012e+00, -1.16823610e+00, -1.26134931e+00],
                 [-6.53122170e-01, -5.85440734e-01, -9.38804269e-01],
                 [ 3.17450538e-01,
                                   1.87322721e+00,
                                                     2.88308413e-02],
                 [ 1.08488012e+00,
                                    1.73663454e+00,
                                                     1.31901099e+00],
                 [ 8.36594080e-01, -5.39909846e-01, -6.16259232e-01],
                 [-2.91978837e-01, -1.18644845e+00, -1.58389434e+00],
                                                     3.51375878e-01],
                 [-1.54469478e+00, -3.12255407e-01,
                 [-1.19483717e+00,
                                   2.52327602e-01,
                                                     9.96465952e-01],
                 [ 4.75450747e-01,
                                   1.87322721e+00,
                                                     1.31901099e+00],
                 [-1.10455134e+00, -2.21193631e-01,
                                                     2.88308413e-02],
                                                     1.31901099e+00]])
                 [-4.72550504e-01, 1.87322721e+00,
```

```
In [29]: inversed = scaler.inverse_transform(X_test)
print(inversed)
```

```
[[1.85e+02 2.00e+02 8.00e-01]
 [1.33e+03 3.54e+02 1.00e+00]
 [8.10e+02 1.32e+02 1.00e+00]
 [7.40e+02 1.36e+02 6.00e-01]
 [1.45e+03 9.80e+01 6.00e-01]
 [1.48e+03 1.82e+02 9.00e-01]
 [1.25e+02 2.40e+01 1.00e-01]
 [1.10e+03 3.46e+02 1.00e+00]
 [1.50e+02 1.20e+02 7.00e-01]
 [1.29e+03 2.60e+01 2.00e-01]
 [5.20e+02 9.00e+01 3.00e-01]
 [9.50e+02 3.60e+02 6.00e-01]
 [1.29e+03 3.45e+02 1.00e+00]
 [1.18e+03 9.50e+01 4.00e-01]
 [6.80e+02 2.40e+01 1.00e-01]
 [1.25e+02 1.20e+02 7.00e-01]
 [2.80e+02 1.82e+02 9.00e-01]
 [1.02e+03 3.60e+02 1.00e+00]
 [3.20e+02 1.30e+02 6.00e-01]
 [6.00e+02 3.60e+02 1.00e+00]]
```

In [30]: pd.DataFrame(inversed)

Out[30]:

	0	1	2
0	185.0	200.0	8.0
1	1330.0	354.0	1.0
2	810.0	132.0	1.0
3	740.0	136.0	0.6
4	1450.0	98.0	0.6
5	1480.0	182.0	0.9
6	125.0	24.0	0.1
7	1100.0	346.0	1.0
8	150.0	120.0	0.7
9	1290.0	26.0	0.2
10	520.0	90.0	0.3
11	950.0	360.0	0.6
12	1290.0	345.0	1.0
13	1180.0	95.0	0.4
14	680.0	24.0	0.1
15	125.0	120.0	0.7
16	280.0	182.0	0.9
17	1020.0	360.0	1.0
18	320.0	130.0	0.6
19	600.0	360.0	1.0

In [ ]: