predictive_maintainance_analysis

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1 Predictive Maintenance

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2 Stages of Data Science

1) Data Collection

2) Exploratory Data Analysis (visual and Descriptive)

3) Feature Engineering (Data Preprocessing)

4) Model Creation and Evaluation

5) Model Deployment

[1]:
```
import os
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib
import warnings
from pandas_profiling import ProfileReport
from sklearn.preprocessing import (LabelEncoder,OneHotEncoder,MaxAbsScaler)

from sklearn.metrics import silhouette_score
from sklearn.neighbors import NearestNeighbors
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SVMSMOTE
from sklearn.metrics import f1_score, precision_score, recall_score,␣
↪accuracy_score,roc_auc_score,confusion_matrix

from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import (
    GradientBoostingClassifier,
    RandomForestClassifier,
)
```

```
from catboost import CatBoostClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neural_network import MLPClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
```

```
C:\Users\Yash Mayur\AppData\Local\Temp\ipykernel_12308\1597575372.py:8:
DeprecationWarning: `import pandas_profiling` is going to be deprecated by April
1st. Please use `import ydata_profiling` instead.
  from pandas_profiling import ProfileReport
```

3 1) Data Collection

[40]:
```
df = pd.read_csv('ai4i2020.csv')
df.head(10)
```

[40]:
```
   UDI Product ID Type  Air temperature [K]  Process temperature [K]  \
0    1     M14860    M                298.1                    308.6
1    2     L47181    L                298.2                    308.7
2    3     L47182    L                298.1                    308.5
3    4     L47183    L                298.2                    308.6
4    5     L47184    L                298.2                    308.7
5    6     M14865    M                298.1                    308.6
6    7     L47186    L                298.1                    308.6
7    8     L47187    L                298.1                    308.6
8    9     M14868    M                298.3                    308.7
9   10     M14869    M                298.5                    309.0

   Rotational speed [rpm]  Torque [Nm]  Tool wear [min]  Machine failure  TWF  \
0                    1551         42.8                0                0    0
1                    1408         46.3                3                0    0
2                    1498         49.4                5                0    0
3                    1433         39.5                7                0    0
4                    1408         40.0                9                0    0
5                    1425         41.9               11                0    0
6                    1558         42.4               14                0    0
7                    1527         40.2               16                0    0
8                    1667         28.6               18                0    0
9                    1741         28.0               21                0    0

   HDF  PWF  OSF  RNF
0    0    0    0    0
1    0    0    0    0
2    0    0    0    0
3    0    0    0    0
4    0    0    0    0
```

5	0	0	0	0
6	0	0	0	0
7	0	0	0	0
8	0	0	0	0
9	0	0	0	0

3.1 Feature Description

1)product ID: consisting of a letter L, M, or H for low (50% of all products), medium (30%) and high (20%) as product quality variants and a variant-specific serial number.

2) Type: just the product type L, M or H from column 2.

3) Air Temperature [K]: generated using a random walk process later normalized to a standard deviation of 2 K around 300 K.

4) Process Temperature [K]: generated using a random walk process normalized to a standard deviation of 1 K, added to the air temperature plus 10 K.

5) Rotational Speed [rpm]: calculated from a power of 2860 W, overlaid with a normally distributed noise.

6) Torque [Nm]: torque values are normally distributed around 40 Nm with a SD = 10 Nm and no negative values.

7) Tool Wear [min]: (breakdown and gradual failure of a cutting tool due to regular operation) The quality variants H/M/L add 5/3/2 minutes of tool wear to the used tool in the process.

8) A 'Machine failure' label that indicates, whether the machine has failed in this particular datapoint for any of the following failure modes are true. The machine failure consists of five independent failure modes as follows:

a) Tool wear failure (TWF): the tool will be replaced of fail at a randomly selected tool wear time between 200 - 240 mins (120 times in our dataset). At this point in time, the tool is replaced 69 times, and fails 51 times (randomly assigned).

b) Heat dissipation failure (HDF): heat dissipation causes a process failure, if the difference between air and process temperature is below 8.6 K and the tools rotational speed is below 1380 rpm. This is the case for 115 data points.

c) Power failure (PWF): the product of torque and rotational speed (in rad/s) equals the power required for the process. If this power is below 3500 W or above 9000 W, the process fails, which is the case 95 times in our dataset.

d) Overstrain failure (OSF): if the product of tool wear and torque exceeds 11,000 minNm for the L product variant (12,000 M, 13,000 H), the process fails due to overstrain. This is true for 98 datapoints.

e) Random failures (RNF): each process has a chance of 0,1 % to fail regardless of its process parameters. This is the case for only 5 datapoints, less than could be expected for 10,000 datapoints in our dataset.

3.1.1 Note: If at least one of the above failure modes is true, the process fails and the 'machine failure' label is set to 1. It is therefore not transparent to the machine learning method, which of the failure modes has caused the process to fail.

4 2) Exploratory Data Analysis

[41]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   UDI                      10000 non-null  int64
 1   Product ID               10000 non-null  object
 2   Type                     10000 non-null  object
 3   Air temperature [K]      10000 non-null  float64
 4   Process temperature [K]  10000 non-null  float64
 5   Rotational speed [rpm]   10000 non-null  int64
 6   Torque [Nm]              10000 non-null  float64
 7   Tool wear [min]          10000 non-null  int64
 8   Machine failure          10000 non-null  int64
 9   TWF                      10000 non-null  int64
 10  HDF                      10000 non-null  int64
 11  PWF                      10000 non-null  int64
 12  OSF                      10000 non-null  int64
 13  RNF                      10000 non-null  int64
dtypes: float64(3), int64(9), object(2)
memory usage: 1.1+ MB
```

4.0.1 Acronyms to be considered:

[K]: kelvin

[rpm]: revolutions per minute

[Nm]: newton-meter

[min]: minutes

[42]:
```
# let's find the null values
df.isnull().sum()
```

[42]:
```
UDI                        0
Product ID                 0
Type                       0
Air temperature [K]        0
Process temperature [K]    0
Rotational speed [rpm]     0
Torque [Nm]                0
Tool wear [min]            0
Machine failure            0
TWF                        0
HDF                        0
PWF                        0
OSF                        0
RNF                        0
dtype: int64
```

No null values present

[43]:
```
# Let's get some description of data
df.describe().T
```

[43]:
```
                           count        mean          std     min      25%  \
UDI                      10000.0  5000.50000  2886.895680     1.0  2500.75
Air temperature [K]      10000.0   300.00493     2.000259   295.3   298.30
Process temperature [K]  10000.0   310.00556     1.483734   305.7   308.80
Rotational speed [rpm]   10000.0  1538.77610   179.284096  1168.0  1423.00
Torque [Nm]              10000.0    39.98691     9.968934     3.8    33.20
Tool wear [min]          10000.0   107.95100    63.654147     0.0    53.00
Machine failure          10000.0     0.03390     0.180981     0.0     0.00
TWF                      10000.0     0.00460     0.067671     0.0     0.00
HDF                      10000.0     0.01150     0.106625     0.0     0.00
PWF                      10000.0     0.00950     0.097009     0.0     0.00
OSF                      10000.0     0.00980     0.098514     0.0     0.00
RNF                      10000.0     0.00190     0.043550     0.0     0.00

                            50%      75%      max
UDI                      5000.5  7500.25  10000.0
Air temperature [K]       300.1   301.50    304.5
Process temperature [K]   310.1   311.10    313.8
Rotational speed [rpm]   1503.0  1612.00   2886.0
Torque [Nm]                40.1    46.80     76.6
Tool wear [min]           108.0   162.00    253.0
Machine failure             0.0     0.00      1.0
```

```
TWF                           0.0     0.00      1.0
HDF                           0.0     0.00      1.0
PWF                           0.0     0.00      1.0
OSF                           0.0     0.00      1.0
RNF                           0.0     0.00      1.0
```

[44]:

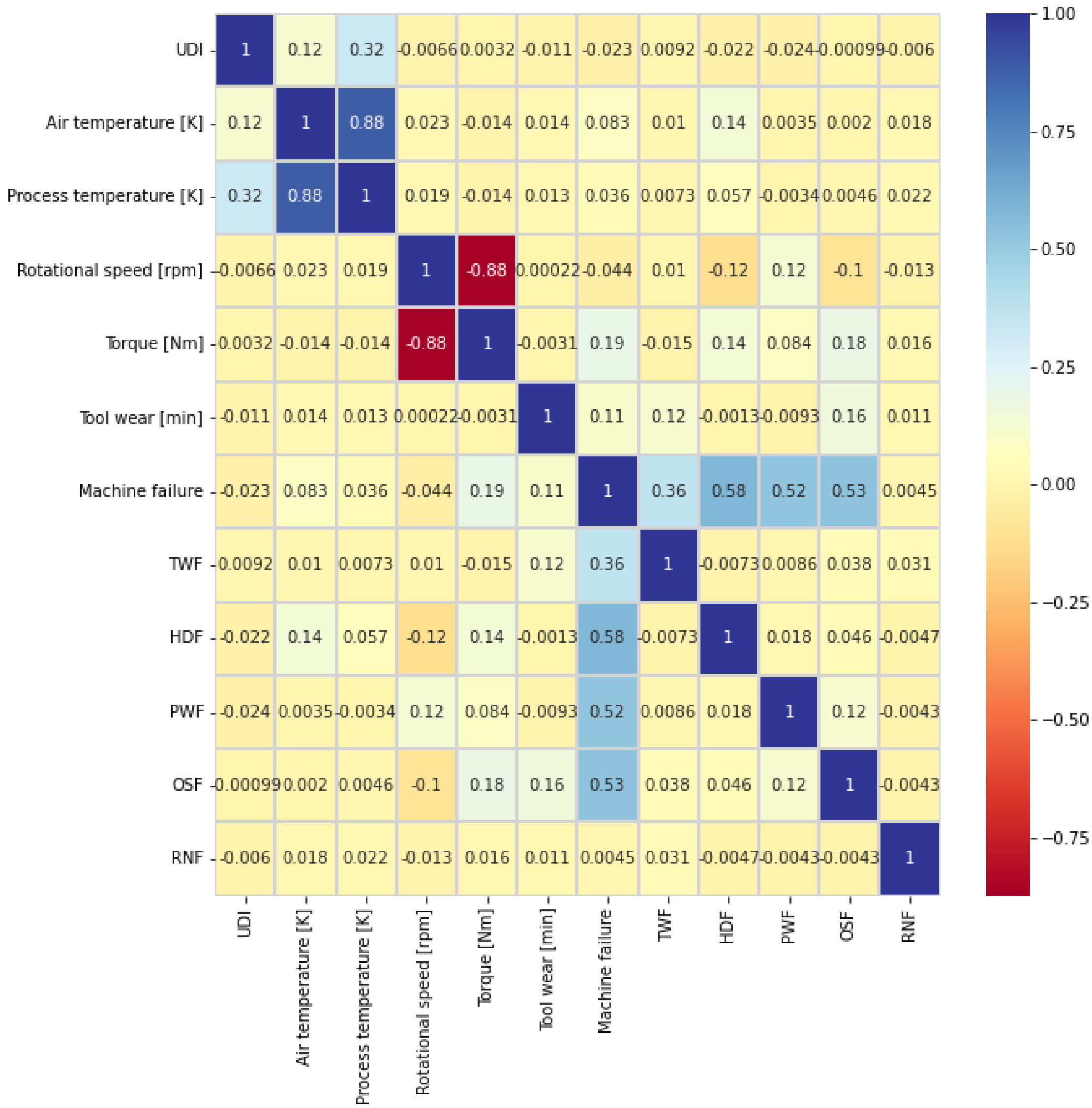
```
# Let's convert int datatype to float for preprocessing purposes

for feature in df.columns:
    if df[feature].dtype != 'O':
        df[feature] = df[feature].astype(float)
```

[45]:

```
# Let's find the correlation of features with each other

plt.figure(figsize=(10,10))
sns.heatmap(df.corr(),
            cmap='RdYlBu',
            annot=True,
            linewidths=0.2,
            linecolor='lightgrey').set_facecolor('white')
```



4.0.2 We can see that there are strongly correlated features namely process temperature and air temperature. Torque and rotational speed are also negatively correlated. We can drop one of the temperatures, but the torque to rotational speed difference might be a indication of a failure, so we'll keep both.

5 So now we will drop some columns which is not usefull

dropping the indices and product id

[46]:
```
df.drop(['UDI','Product ID'],axis=1,inplace=True)
```

Drop the failure modes, as currently we are only interested whether something is failed or not.

[47]:
```
df.drop(['TWF','HDF','PWF','OSF','RNF'],axis=1,inplace=True)
```

Let's check balanced relation of the independent features with thetarget feature

[48]:
```
df_group = df.groupby(['Machine failure'])
df_group.count()
```

[48]:
```
                 Type  Air temperature [K]  Process temperature [K]  \
Machine failure
0.0              9661                 9661                     9661
1.0               339                  339                      339

                 Rotational speed [rpm]  Torque [Nm]  Tool wear [min]
Machine failure
0.0                                9661         9661             9661
1.0                                 339          339              339
```

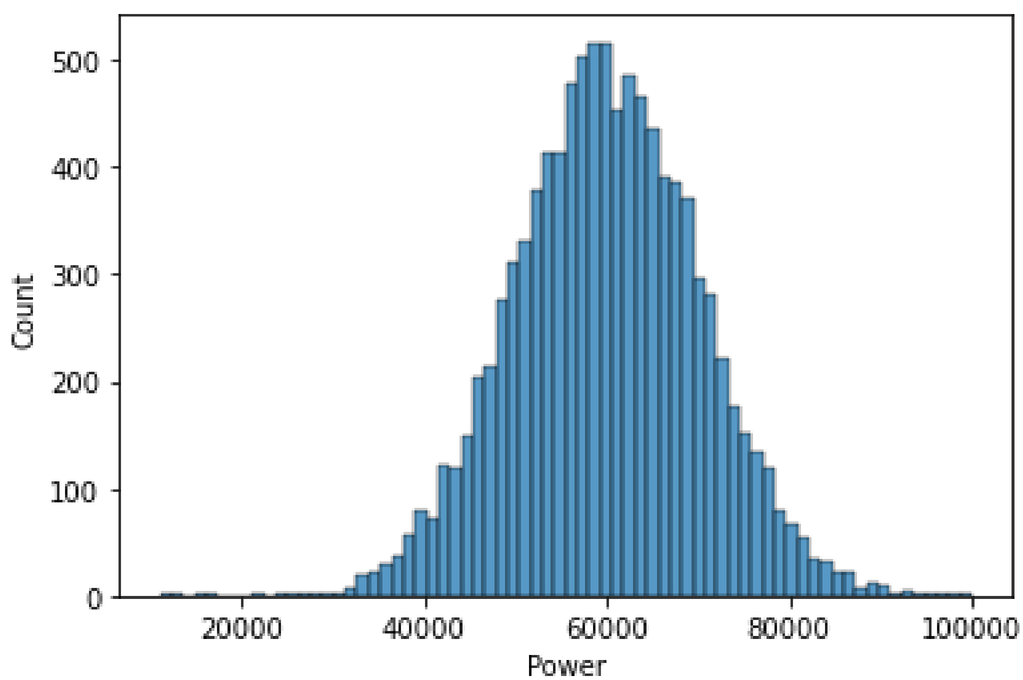
5.0.1 The above table clearly shows that the dataset is imbalanced

6 Let's derive a power attribute using this formula:

Power = Torque × Rotational speed

[49]:
```
df['Power'] = df[['Rotational speed [rpm]', 'Torque [Nm]']].product(axis=1)
sns.histplot(df['Power'])
```

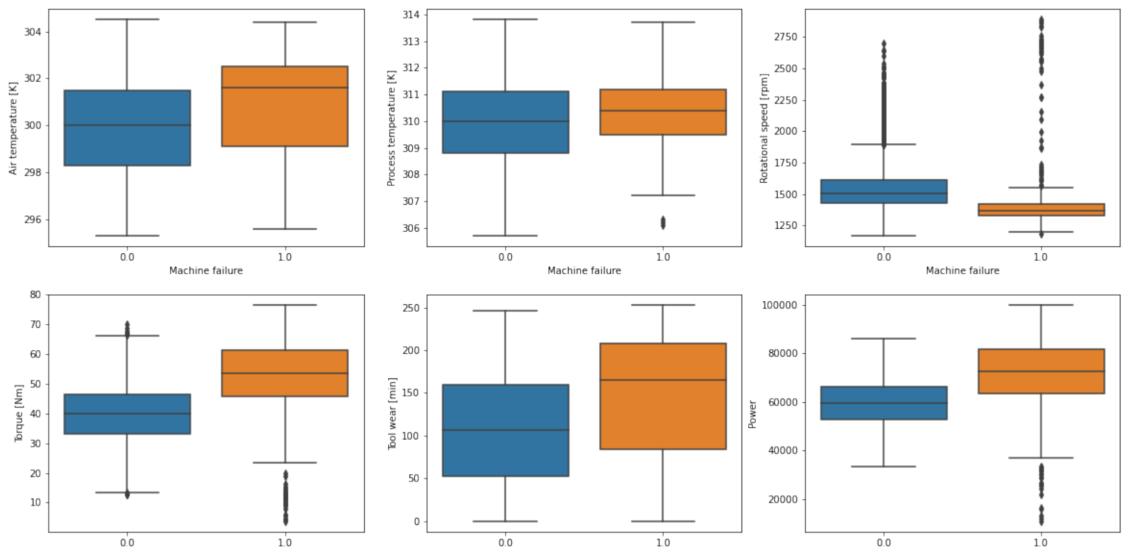
[49]: <AxesSubplot:xlabel='Power', ylabel='Count'>



We get gaussian normal distribution for the power feature

[50]:
```
## Boxplot

fig, ax = plt.subplots(2, 3, figsize=(20, 10))
i=0
for _, col in enumerate(df.columns):
    if col == "Machine failure":
        continue
    elif col == "Type":
        continue
    else:
        sns.boxplot(x="Machine failure", y=col, data=df, ax=ax[i//3][i%3])
        i += 1
```



7 3) Descriptive Analysis

7.0.1 Clustering

[51]:
```
# features to use for clustering
feature_list = [feature for feature in df.columns if df[feature].dtype ==␣
 ↪'float64']
X = df[feature_list]
from sklearn.cluster import KMeans

# K-means clustering
```

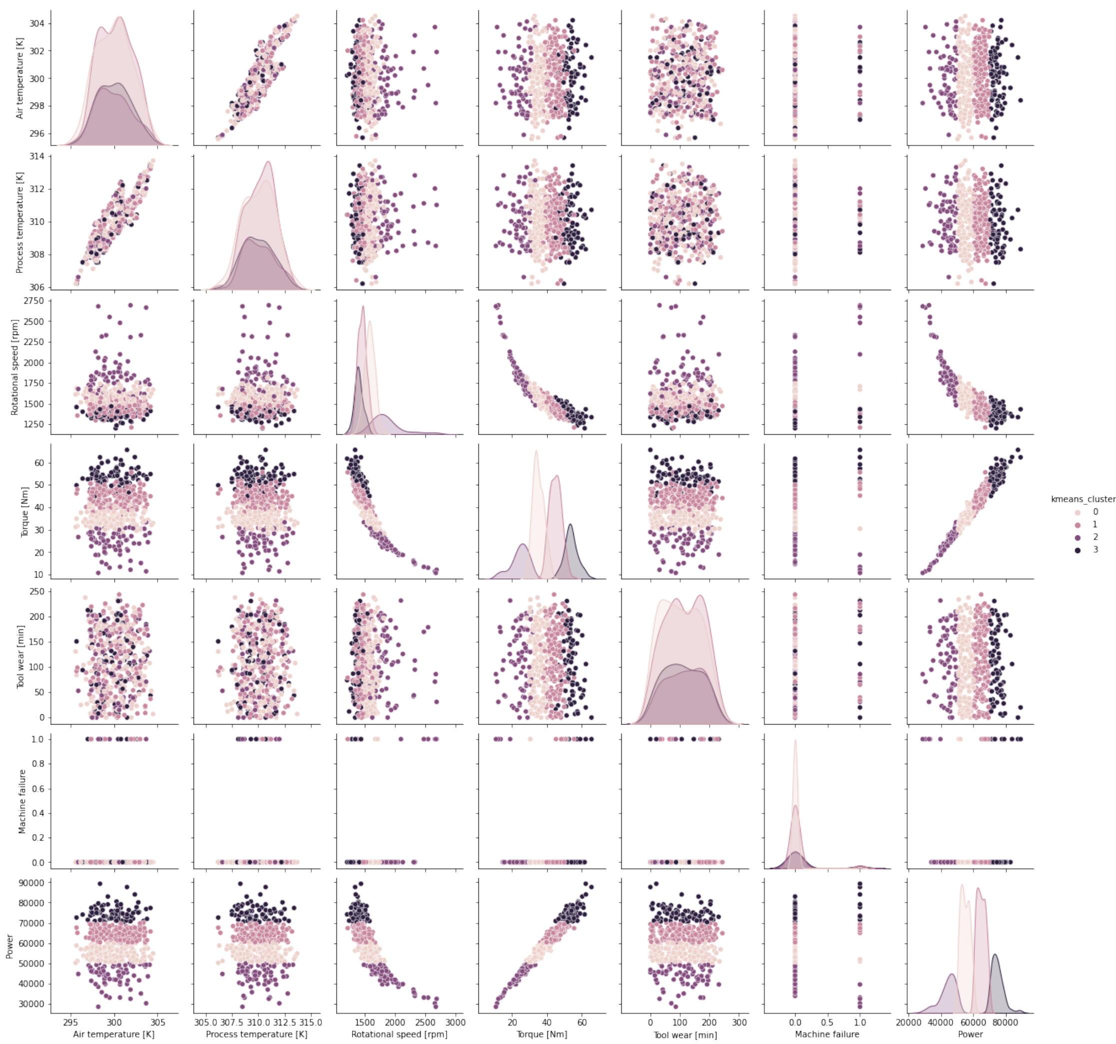
```
kmeans = KMeans(init='random',  n_clusters=4,
                n_init=10, max_iter=300, random_state=42)
kmeans.fit(X)

df["kmeans_cluster"] = kmeans.predict(X)
```

[52]:
```
plt.figure(figsize=(10, 8))

# create a pairplot of the data, colored by cluster label
sns.pairplot(df.sample(frac=0.05), hue="kmeans_cluster", vars=feature_list)
plt.show()
```

<Figure size 720x576 with 0 Axes>



7.1 From the above results we can clearly observe

Process Temperature and Air Temperature have Linear Relationship with each other and both the data has gaussian normal distribution

[53]:
```
# calculate the silhouette coefficient
score = silhouette_score(X, kmeans.predict(X))

print(f"Silhouette Coefficient: {score}")
```

```
Silhouette Coefficient: 0.5191499897517547
```

7.1.1 We can say that the clusters are well apart from each other as the silhouette score is closer to 1.

[33]:
```
## Let's convert the dataframe which can be used further in our project

os.makedirs(os.getcwd(),exist_ok=True)
df.to_csv("data.csv",header=True,index=False)
```

8 4) Feature Engineering (Data Pre-processing) and Feature Selection

8.0.1 Encoding of Categorical Feature i.e. Type

Use any one only

1) Label Encoding or 2) One Hot Encoding

[17]:
```
## Label Encoding

le = LabelEncoder()
df['Type'] = le.fit_transform(df['Type'])
df.head()
```

[17]:

	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	\
0	2	298.1	308.6	1551.0	
1	1	298.2	308.7	1408.0	
2	1	298.1	308.5	1498.0	
3	1	298.2	308.6	1433.0	
4	1	298.2	308.7	1408.0	

	Torque [Nm]	Tool wear [min]	Machine failure	Power	kmeans_cluster
0	42.8	0.0	0.0	66382.8	1
1	46.3	3.0	0.0	65190.4	1
2	49.4	5.0	0.0	74001.2	3
3	39.5	7.0	0.0	56603.5	0
4	40.0	9.0	0.0	56320.0	0

[54]:
```
# One Hot Encoding

frame = pd.get_dummies(data=df['Type'],drop_first=True)
df.drop(columns='Type',axis=1,inplace=True)
df['L'] = frame['L']
df['M'] = frame['M']
df.head()
```

[54]:
```
   Air temperature [K]  Process temperature [K]  Rotational speed [rpm]  \
0                298.1                    308.6                  1551.0
1                298.2                    308.7                  1408.0
2                298.1                    308.5                  1498.0
3                298.2                    308.6                  1433.0
4                298.2                    308.7                  1408.0

   Torque [Nm]  Tool wear [min]  Machine failure    Power  kmeans_cluster  L  \
0         42.8              0.0              0.0  66382.8               1  0
1         46.3              3.0              0.0  65190.4               1  1
2         49.4              5.0              0.0  74001.2               3  1
3         39.5              7.0              0.0  56603.5               0  1
4         40.0              9.0              0.0  56320.0               0  1

   M
0  1
1  0
2  0
3  0
4  0
```

[55]:
```
X = df.drop(columns=['Machine failure','kmeans_cluster'],axis=1)
y = df['Machine failure']
X
```

[55]:
```
      Air temperature [K]  Process temperature [K]  Rotational speed [rpm]  \
0                   298.1                    308.6                  1551.0
1                   298.2                    308.7                  1408.0
2                   298.1                    308.5                  1498.0
3                   298.2                    308.6                  1433.0
4                   298.2                    308.7                  1408.0
…                     …                        …                       …
9995                298.8                    308.4                  1604.0
9996                298.9                    308.4                  1632.0
9997                299.0                    308.6                  1645.0
9998                299.0                    308.7                  1408.0
9999                299.0                    308.7                  1500.0

      Torque [Nm]  Tool wear [min]    Power  L  M
```

```
0              42.8              0.0  66382.8  0  1
1              46.3              3.0  65190.4  1  0
2              49.4              5.0  74001.2  1  0
3              39.5              7.0  56603.5  1  0
4              40.0              9.0  56320.0  1  0
…              …              …       … .. ..
9995           29.5             14.0  47318.0  0  1
9996           31.8             17.0  51897.6  0  0
9997           33.4             22.0  54943.0  0  1
9998           48.5             25.0  68288.0  0  0
9999           40.2             30.0  60300.0  0  1

[10000 rows x 8 columns]
```

[59]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25,␣
↪random_state = 42)

X_test.shape
```

[59]: (2500, 8)

8.0.2 As analysed and Mentioned earlier that the dataset is imbalanced so we have to use SMOTE technique on training data inorder to make balance data

[60]:
```
oversample = SVMSMOTE(random_state = 42)

X_train, y_train = oversample.fit_resample(X_train, y_train)
```

[61]:
```
scale = MaxAbsScaler()
X_train = scale.fit_transform(X_train)
X_test = scale.transform(X_test)
```

9 5) Model Creation and Evaluation

9.0.1 a) Logistic Regression

[62]:
```
# Logistic Regression

model_dict = dict()

model = LogisticRegression().fit(X_train,y_train)
y_pred = model.predict(X_test) # These are the predictions from the test data.
y_pred
```

[62]: array([0., 0., 0., …, 0., 0., 0.])

[63]:
```
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred, average='weighted')
precision = precision_score(y_test, y_pred, average='weighted')
f1s = f1_score(y_test, y_pred, average='weighted')
ROC_AUC = roc_auc_score(y_test, model.predict_proba(X_test)[:,1],␣
 ↪average='weighted')
confusion_mat = confusion_matrix(y_test,y_pred)

model_dict.update({"Logistic Regression":accuracy})
print("Accuracy: "+ "{:.2%}".format(accuracy))
print("Recall: "+ "{:.2%}".format(recall))
print("Precision: "+ "{:.2%}".format(precision))
print("F1-Score: "+ "{:.2%}".format(f1s))
print("ROC AUC score: "+ "{:.2%}".format(ROC_AUC))
print("Confusion Matrix: \n")
confusion_mat
```

```
Accuracy: 88.24%
Recall: 88.24%
Precision: 96.59%
F1-Score: 91.65%
ROC AUC score: 86.40%
Confusion Matrix:
```

[63]:
```
array([[2156,  272],
       [  22,   50]], dtype=int64)
```

9.0.2 b) Decision Tree

[64]:
```
# Decision Tree

model = DecisionTreeClassifier().fit(X_train,y_train)
y_pred = model.predict(X_test)
y_pred
```

[64]:
```
array([0., 0., 0., …, 0., 0., 0.])
```

[65]:
```
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred, average='weighted')
precision = precision_score(y_test, y_pred, average='weighted')
f1s = f1_score(y_test, y_pred, average='weighted')
ROC_AUC = roc_auc_score(y_test, model.predict_proba(X_test)[:,1],␣
 ↪average='weighted')
confusion_mat = confusion_matrix(y_test,y_pred)

model_dict.update({"Decision Tree":accuracy})
```

```
print("Accuracy: "+ "{:.2%}".format(accuracy))
print("Recall: "+ "{:.2%}".format(recall))
print("Precision: "+ "{:.2%}".format(precision))
print("F1-Score: "+ "{:.2%}".format(f1s))
print("ROC AUC score: "+ "{:.2%}".format(ROC_AUC))
print("Confusion Matrix: \n")
confusion_mat
```

```
Accuracy: 96.20%
Recall: 96.20%
Precision: 97.35%
F1-Score: 96.66%
ROC AUC score: 82.55%
Confusion Matrix:
```

[65]:
```
array([[2356,   72],
       [  23,   49]], dtype=int64)
```

9.0.3 c) Random Forest Classifier

[66]:
```
# Random Forest Classifier

model = RandomForestClassifier(n_estimators =␣
↪100,n_jobs=-1,random_state=42,bootstrap=True,).fit(X_train,y_train)
y_pred = model.predict(X_test)
y_pred
```

[66]:
```
array([0., 0., 0., …, 0., 0., 0.])
```

[67]:
```
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred, average='weighted')
precision = precision_score(y_test, y_pred, average='weighted')
f1s = f1_score(y_test, y_pred, average='weighted')
ROC_AUC = roc_auc_score(y_test, model.predict_proba(X_test)[:,1],␣
↪average='weighted')
confusion_mat = confusion_matrix(y_test,y_pred)

model_dict.update({"Random Forest Classifier":accuracy})
print("Accuracy: "+ "{:.2%}".format(accuracy))
print("Recall: "+ "{:.2%}".format(recall))
print("Precision: "+ "{:.2%}".format(precision))
print("F1-Score: "+ "{:.2%}".format(f1s))
print("ROC AUC score: "+ "{:.2%}".format(ROC_AUC))
print("Confusion Matrix: \n")
confusion_mat
```

```
Accuracy: 97.64%
Recall: 97.64%
Precision: 98.07%
F1-Score: 97.81%
ROC AUC score: 96.88%
Confusion Matrix:
```

[67]:
```
array([[2386,   42],
       [  17,   55]], dtype=int64)
```

9.0.4 d) Gradient Boosting classifier

[68]:
```
model = GradientBoostingClassifier().fit(X_train,y_train)
y_pred = model.predict(X_test)
y_pred
```

[68]:
```
array([0., 0., 0., …, 0., 0., 0.])
```

[69]:
```
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred, average='weighted')
precision = precision_score(y_test, y_pred, average='weighted')
f1s = f1_score(y_test, y_pred, average='weighted')
ROC_AUC = roc_auc_score(y_test, model.predict_proba(X_test)[:,1],␣
 ↪average='weighted')
confusion_mat = confusion_matrix(y_test,y_pred)

model_dict.update({"Gradient Boosting":accuracy})
print("Accuracy: "+ "{:.2%}".format(accuracy))
print("Recall: "+ "{:.2%}".format(recall))
print("Precision: "+ "{:.2%}".format(precision))
print("F1-Score: "+ "{:.2%}".format(f1s))
print("ROC AUC score: "+ "{:.2%}".format(ROC_AUC))
print("Confusion Matrix: \n")
confusion_mat
```

```
Accuracy: 96.80%
Recall: 96.80%
Precision: 97.98%
F1-Score: 97.23%
ROC AUC score: 97.07%
Confusion Matrix:
```

[69]:
```
array([[2360,   68],
       [  12,   60]], dtype=int64)
```

9.0.5 e) K Neighbors Classifier

[70]:
```
model = KNeighborsClassifier(n_neighbors=2).fit(X_train, y_train)
y_pred = model.predict(X_test)
y_pred
```

[70]:
```
array([0., 0., 0., …, 0., 0., 0.])
```

[71]:
```
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred, average='weighted')
precision = precision_score(y_test, y_pred, average='weighted')
f1s = f1_score(y_test, y_pred, average='weighted')
ROC_AUC = roc_auc_score(y_test, model.predict_proba(X_test)[:,1],␣
 ↪average='weighted')
confusion_mat = confusion_matrix(y_test,y_pred)

model_dict.update({"KNN Classifier":accuracy})
print("Accuracy: "+ "{:.2%}".format(accuracy))
print("Recall: "+ "{:.2%}".format(recall))
print("Precision: "+ "{:.2%}".format(precision))
print("F1-Score: "+ "{:.2%}".format(f1s))
print("ROC AUC score: "+ "{:.2%}".format(ROC_AUC))
print("Confusion Matrix: \n")
confusion_mat
```

```
Accuracy: 94.96%
Recall: 94.96%
Precision: 97.19%
F1-Score: 95.84%
ROC AUC score: 85.81%
Confusion Matrix:
```

[71]:
```
array([[2323,  105],
       [  21,   51]], dtype=int64)
```

9.0.6 f) Gaussian Naive Bayes Classifier

[72]:
```
model = GaussianNB().fit(X_train, y_train)
y_pred = model.predict(X_test)
y_pred
```

[72]:
```
array([0., 0., 0., …, 0., 0., 0.])
```

[73]:
```
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred, average='weighted')
precision = precision_score(y_test, y_pred, average='weighted')
```

```
f1s = f1_score(y_test, y_pred, average='weighted')
ROC_AUC = roc_auc_score(y_test, model.predict_proba(X_test)[:,1],␣
 ↪average='weighted')
confusion_mat = confusion_matrix(y_test,y_pred)

model_dict.update({"Gaussian Naive Bayes":accuracy})
print("Accuracy: "+ "{:.2%}".format(accuracy))
print("Recall: "+ "{:.2%}".format(recall))
print("Precision: "+ "{:.2%}".format(precision))
print("F1-Score: "+ "{:.2%}".format(f1s))
print("ROC AUC score: "+ "{:.2%}".format(ROC_AUC))
print("Confusion Matrix: \n")
confusion_mat
```

```
Accuracy: 88.56%
Recall: 88.56%
Precision: 96.60%
F1-Score: 91.85%
ROC AUC score: 88.84%
Confusion Matrix:
```

[73]:
```
array([[2164,  264],
       [  22,   50]], dtype=int64)
```

9.0.7 g) Cat Boost Classifier

[74]:
```
model = CatBoostClassifier(verbose = False).fit(X_train,y_train)
y_pred = model.predict(X_test)
y_pred
```

[74]:
```
array([0., 0., 0., …, 0., 0., 0.])
```

[75]:
```
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred, average='weighted')
precision = precision_score(y_test, y_pred, average='weighted')
f1s = f1_score(y_test, y_pred, average='weighted')
ROC_AUC = roc_auc_score(y_test, model.predict_proba(X_test)[:,1],␣
 ↪average='weighted')
confusion_mat = confusion_matrix(y_test,y_pred)

model_dict.update({"Catboost Classifier":accuracy})
print("Accuracy: "+ "{:.2%}".format(accuracy))
print("Recall: "+ "{:.2%}".format(recall))
print("Precision: "+ "{:.2%}".format(precision))
print("F1-Score: "+ "{:.2%}".format(f1s))
print("ROC AUC score: "+ "{:.2%}".format(ROC_AUC))
```

```
print("Confusion Matrix: \n")
confusion_mat
```

```
Accuracy: 97.96%
Recall: 97.96%
Precision: 98.28%
F1-Score: 98.09%
ROC AUC score: 97.07%
Confusion Matrix:
```

[75]:
```
array([[2392,   36],
       [  15,   57]], dtype=int64)
```

9.0.8 h) Nueral Network MLP Classifier

[76]:
```
model = MLPClassifier(hidden_layer_sizes = (100,100,), activation='relu',␣
  ↪solver='adam', batch_size=2000,verbose=0).fit(X_train,y_train)
y_pred = model.predict(X_test)
```

```
C:\Users\Yash Mayur\anaconda3\lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:692:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

[77]:
```
accuracy = accuracy_score(y_test, y_pred)
recall = recall_score(y_test, y_pred, average='weighted')
precision = precision_score(y_test, y_pred, average='weighted')
f1s = f1_score(y_test, y_pred, average='weighted')
ROC_AUC = roc_auc_score(y_test, model.predict_proba(X_test)[:,1],␣
  ↪average='weighted')
confusion_mat = confusion_matrix(y_test,y_pred)

model_dict.update({"Nueral Network Classifier":accuracy})
print("Accuracy: "+ "{:.2%}".format(accuracy))
print("Recall: "+ "{:.2%}".format(recall))
print("Precision: "+ "{:.2%}".format(precision))
print("F1-Score: "+ "{:.2%}".format(f1s))
print("ROC AUC score: "+ "{:.2%}".format(ROC_AUC))
print("Confusion Matrix: \n")
confusion_mat
```

```
Accuracy: 88.04%
Recall: 88.04%
Precision: 96.73%
F1-Score: 91.55%
```

```
ROC AUC score: 91.51%
Confusion Matrix:
```

[77]:
```
array([[2148,  280],
       [  19,   53]], dtype=int64)
```

10 6) Best Model to use

[78]:
```python
sorted_dict = dict(sorted(model_dict.items(),key=lambda x:x[1],reverse=True))
Model_name = list(sorted_dict.keys())[0]
Model_accuracy = list(sorted_dict.values())[0]

sent = "The Best Model is {0} and its accuracy is {1}".
 ↪format(Model_name,Model_accuracy*100)
print(sent)
```

```
The Best Model is Catboost Classifier and its accuracy is 97.96000000000001
```

11 7) Quick Data Analysis Report

[ ]:
```python
dataframe = pd.read_csv('ai4i2020.csv')
Report = ProfileReport(dataframe,explorative=True)
Report
```

[ ]:
```python
Report.to_file("Data_Analysis_Report.pdf")
```