Factory Machine Failure Classification

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Module Code: ST1511 AI and Machine Learning

References (In Harvard format):

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Project Objective

Use a supervised classification machine learning model to predict if a machine will fail or not

Background Information

Dataset is collected from a factory. Inside the factory, there are many machines, and they might break down after using for some time. Therefore, it is useful to build a prediction model in order to predict which machine will possibly fail before it actually fails, so that the technician can replace it without interruption the production.

Potential Reasons why Machine fails

- Tool wear failure: Machines experiencing physical wear and tear like bearing failure
- Overheating: Machines overheat and causes circuits in the machine to get damaged
- Shaft looseness: Machines with high horsepower will cause the machine to overwork and failure

Initialising Libraries and Variables

In [ ]:
```python
# Basic libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from pandas_profiling import ProfileReport
import seaborn as sns

# SKLEARN Libraries
# Preprocessing
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import FunctionTransformer, StandardScaler, OrdinalEncoder
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer, SimpleImputer

# Model Selection
from sklearn.model_selection import (
    train_test_split,
    cross_validate,
    cross_val_score,
    GridSearchCV,
    RandomizedSearchCV,
    cross_val_predict,
    learning_curve,
    StratifiedKFold,
)
from sklearn.metrics import classification_report, confusion_matrix, RocCurveDisplay
from sklearn.tree import export_graphviz
from sklearn.tree import plot_tree

# Models
from sklearn.dummy import DummyClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.linear_model import Perceptron
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import RidgeClassifier
from sklearn.linear_model import RidgeClassifierCV
from sklearn.linear_model import SGDClassifier

# IMBLEARN
from imblearn.pipeline import Pipeline
from imblearn.over_sampling import RandomOverSampler

# Pickle Library = Saving Models
import pickle
```

In [ ]:
```python
# This is used to set the seed for the RNG splitter later on.
random_state = 32
```

Loading Datasets

In [ ]:
```python
df = pd.read_csv("./factory_data (classification).csv", sep=",")
```

```
df.head()
```

Out[ ]:

	Unique ID	Product ID	Quality	Ambient T (C)	Process T (C)	Rotation Speed (rpm)	Torque (Nm)	Tool Wear (min)	Machine Status
0	1	K12965	M	24.95	35.45	1551.0	42.8	0	0
1	2	Z62710	L	25.05	35.55	1408.0	46.3	3	0
2	3	T20224	L	24.95	35.35	1498.0	49.4	5	0
3	4	Z33024	L	25.05	35.45	1433.0	39.5	7	0
4	5	Z52839	L	25.05	35.55	1408.0	40.0	9	0

Exploratory Data Analysis

We will begin by conducting an exploratory data analysis of the data, to gain a better understanding of the characteristics of the dataset.

This is a dataset collected from a manufacturing company, it contains 20000 data points with 9 columns.

Unique ID: Unique identifier ranging from 1 to 20000
Product ID: The serial number of product
Quality: Consist of letter L, M and H for low, medium and high quality
Ambient T: Environment temperature
Process T: Machine temperature
Rotation Speed: Rotational speed of machine when running
Torque: Measure of the turning force
Tool Wear: Tool wear time estimated for the machine
Machine Status: Labels indicate machine failure or not, 1 means failure, 0 means normal.

Data Exploration

To prevent mutation of our original data, we will make a copy of our data to perform eda on it.

In [ ]:
```
df_eda = df.copy()
```

Descriptive Statistics

In [ ]:
```
df_eda.shape
```

Out[ ]:
```
(20000, 9)
```

There are 20000 rows and 9 columns in the entire data set.

In [ ]:
```
df_eda.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Unique ID             20000 non-null  int64  
 1   Product ID            20000 non-null  object 
 2   Quality               19009 non-null  object 
 3   Ambient T (C)         20000 non-null  float64
 4   Process T (C)         19600 non-null  float64
 5   Rotation Speed (rpm)  18812 non-null  float64
 6   Torque (Nm)           20000 non-null  float64
 7   Tool Wear (min)       20000 non-null  int64  
 8   Machine Status        20000 non-null  int64  
dtypes: float64(4), int64(3), object(2)
memory usage: 1.4+ MB
```

Observations

- The shape of dataset is (20000, 9) whereby there is 20000 observations and 9 columns. (8 Features + 1 Target Variable: "Machine Status")
- Datatype of all columns are numeric except Product ID and Quality
- Missing values is observed in "Quality", "Process T (C)" and "Rotation Speed (rpm)" columns which is around 4.955%, 2% and 5.94% (991, 400 and 1188 Missing Values respectively) of the entire dataset.

We note that the columns "Quality", "Process T (C)", "Rotation Speed (rpm)" has missing values. We will need to handle this later

Target Variable

In [ ]:
```
df_eda["Machine Status"].unique()
```

Out[ ]:
```
array([0, 1], dtype=int64)
```

We also have to note that machine status is a numerical value that is either 1 or 0.
0: Machine working
1: Machine fail

We can convert the values into a string for us to easily view for our future eda using the .replace() so that
Working: Machine working
Fail: Machine fail

In [ ]:
```
df_eda["Machine Status"] = (
    df_eda["Machine Status"].replace(0, "Working").replace(1, "Fail")
)
```

Data Information

In [ ]:
```
descriptive_stats = df_eda.describe(include="all").T
descriptive_stats["Proportion of Most Frequent Value"] = (
    descriptive_stats["freq"] / len(df_eda) * 100
)
descriptive_stats.sort_values("Proportion of Most Frequent Value", ascending=False)
```

Out[ ]:

	count	unique	top	freq	mean	std	min	25%	50%	75%
Machine Status	20000	2	Working	19322	NaN	NaN	NaN	NaN	NaN	NaN
Quality	19009	3	L	11390	NaN	NaN	NaN	NaN	NaN	NaN
Product ID	20000	19408	T21950	3	NaN	NaN	NaN	NaN	NaN	NaN
Unique ID	20000.0	NaN	NaN	NaN	10000.5	5773.647028	1.0	5000.75	10000.5	15000.25
Ambient T (C)	20000.0	NaN	NaN	NaN	26.90493	2.000834	22.15	25.25	26.95	28.45
Process T (C)	19600.0	NaN	NaN	NaN	36.904291	1.483647	32.55	35.75	36.95	37.95
Rotation Speed (rpm)	18812.0	NaN	NaN	NaN	1538.795397	178.674963	1168.0	1423.0	1503.0	1613.0
Torque (Nm)	20000.0	NaN	NaN	NaN	39.98691	9.968684	3.8	33.2	40.1	46.8
Tool Wear (min)	20000.0	NaN	NaN	NaN	107.951	63.652555	0.0	53.0	108.0	162.0

From looking at the most frequent value of each column, we note that:

- almost all the machines are working, and the machine status does not appear to be balanced.

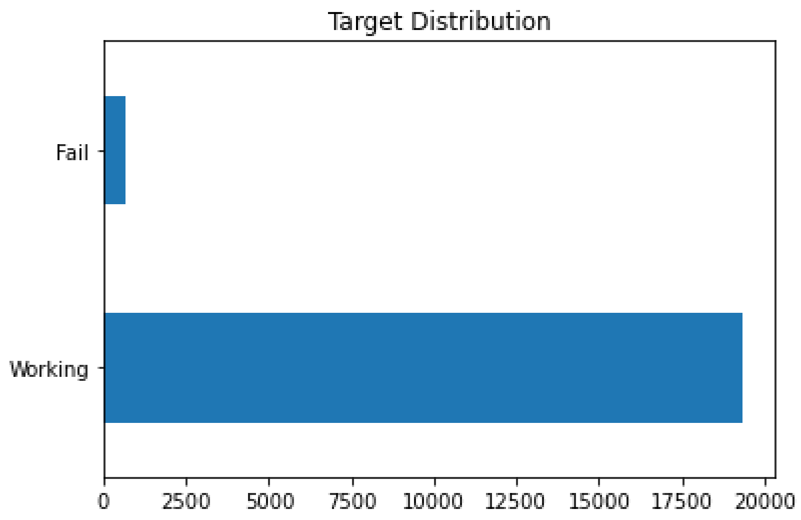
Target Label

Our target label is the Machine Status column. It is a binary column with two values:

False: Machine working

True: Machine fail

In [ ]:
```python
ax = (
    df_eda["Machine Status"]
    .value_counts()
    .plot(kind="barh", title="Target Distribution")
)
```



As we can see, the machine status distribution is imbalanced, with almost all machines working. This is a concern and we will have to take note of this.

Pandas-Profiling

Pandas-Profiling is a convenient tool to quickly explore the datasets along with some alerts/warnings about the dataset.

In [ ]:
```
prof = ProfileReport(df_eda, explorative=True)
# prof.to_notebook_iframe()
# prof.to_file(output_file='factory_analysis.html')
```

In [ ]:
```
# Summary 1
print("Summary")
print(
    f"1. Number of UniqueID: {len(np.unique(df_eda['Unique ID']))}, Length of Dataset: {len(d
print(
    f"2. Number of ProductID: {len(np.unique(df_eda['Product ID']))}")
print(
    f"3. Missing Values: \n{df_eda.isna().sum()}")
print(
    f"4. Unique Values in Quality Column: {df_eda['Quality'].unique()}")
print(
    f"5. Number of zeros in Tool Wear (min): {(df_eda['Tool Wear (min)'] == 0).sum()}\nPercen
```

```
Summary
1. Number of UniqueID: 20000, Length of Dataset: 20000
2. Number of ProductID: 19408
3. Missing Values:
Unique ID               0
Product ID              0
Quality               991
Ambient T (C)           0
Process T (C)         400
Rotation Speed (rpm)   1188
Torque (Nm)             0
Tool Wear (min)         0
Machine Status          0
dtype: int64
4. Unique Values in Quality Column: ['M' 'L' nan 'H']
5. Number of zeros in Tool Wear (min): 240
Percentage of dataset: 1.2%
```

Summary:

1. Unique ID is a UNIQUE KEY which means it is not a feature to describe the machine functions
2. Product ID has a high cardinality: 19408 distinct values this means it is a primary key and it is not a feature to describe the machine properly
3. Data Cleaning/ Imputation is needed to treat missing values for Quality, Process T (C), Rotation Speed (rpm).
4. Encode the Quality features into Ordinal Encoding as Quality is a ordinal value ['L','M','H'].
5. Tool Wear (min) has 240 zeros which is 1.2% of the entire dataset.

Univariate Analysis

We will begin with a univariate analysis, analysing the distribution of each variable.

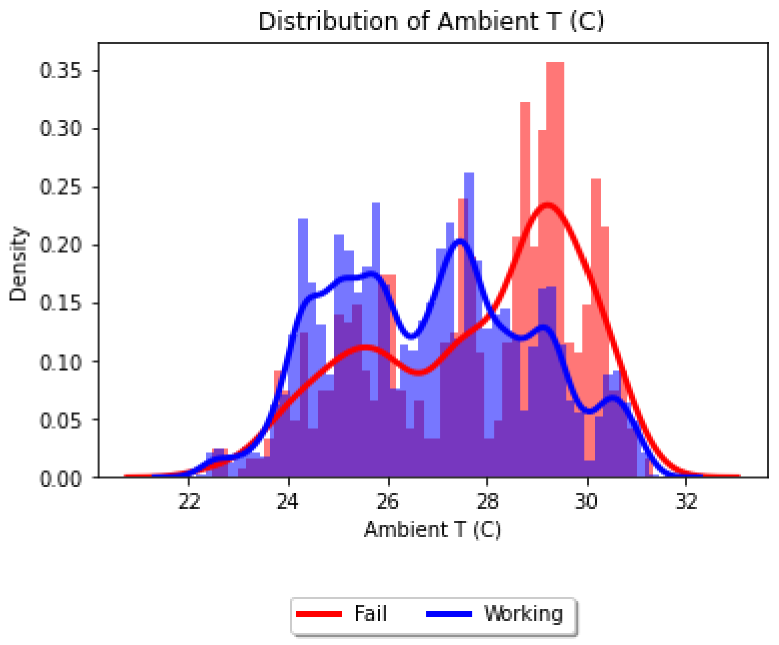
Distributions

We will plot and see the distribution of the different variables and how it relates to Machine Status

Ambient T (C)

Distribution of Ambient T is not very obvious. But it seems like if the temperature of Ambient is larger than 28, the machine will generally fail

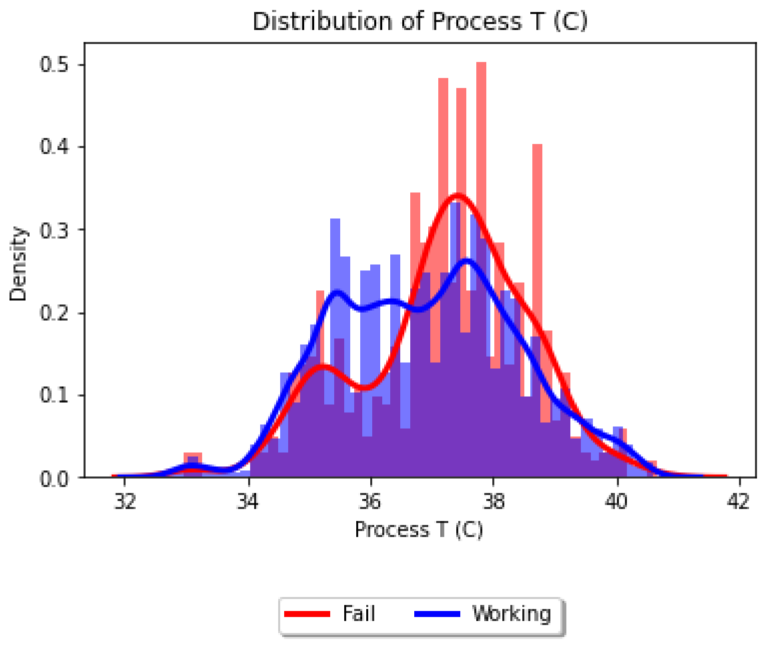
In [ ]:
```
# Ambient T (C)
plt.hist(
    df[df["Machine Status"] == 1]["Ambient T (C)"],
    density=True,
    bins=50,
    color="#ff000088",
)
plt.hist(
    df[df["Machine Status"] == 0]["Ambient T (C)"],
    density=True,
    bins=50,
    color="#0000ff88",
)
sns.kdeplot(df[df["Machine Status"] == 1]["Ambient T (C)"], lw=3, color="#ff0000")
sns.kdeplot(df[df["Machine Status"] == 0]["Ambient T (C)"], lw=3, color="#0000ff")
plt.legend(
    np.unique(df_eda["Machine Status"]),
    loc="upper center",
    bbox_to_anchor=(0.5, -0.25),
    fancybox=True,
    shadow=True,
    ncol=3,
)
plt.title("Distribution of Ambient T (C)")
plt.show()
```



Process T (C)

Distribution of Process T is not very obvious and the distribution is hard to distinguish between the machine working or failing

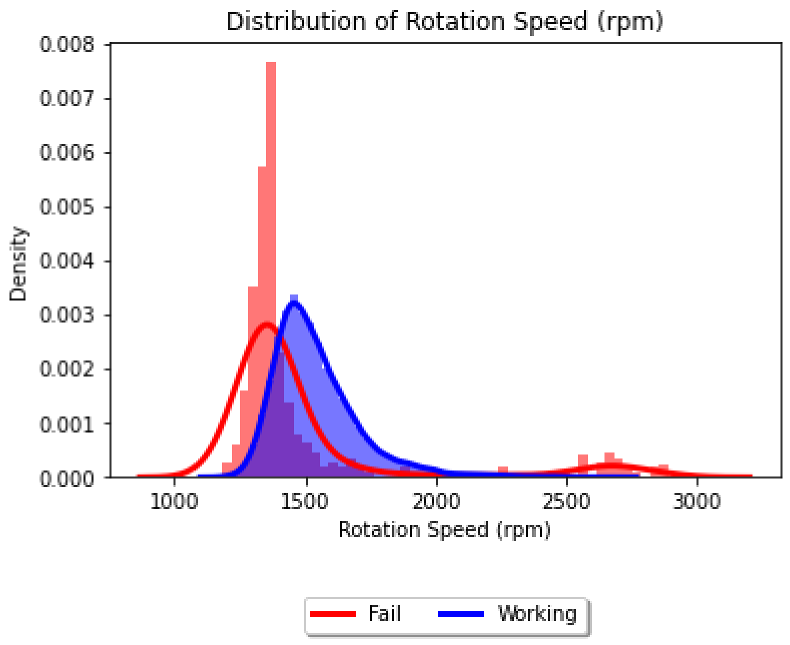
```
In [ ]:
# Process T (C)
plt.hist(
    df[df["Machine Status"] == 1]["Process T (C)"],
    density=True,
    bins=50,
    color="#ff000088",
)
plt.hist(
    df[df["Machine Status"] == 0]["Process T (C)"],
    density=True,
    bins=50,
    color="#0000ff88",
)
sns.kdeplot(df[df["Machine Status"] == 1]["Process T (C)"], lw=3, color="#ff0000")
sns.kdeplot(df[df["Machine Status"] == 0]["Process T (C)"], lw=3, color="#0000ff")
plt.legend(
    np.unique(df_eda["Machine Status"]),
    loc="upper center",
    bbox_to_anchor=(0.5, -0.25),
    fancybox=True,
    shadow=True,
    ncol=3,
)
plt.title("Distribution of Process T (C)")
plt.show()
```



Rotation Speed (rpm)

Distribution of Rotation Speed (rpm) very skewed to the right. But generally, the lower the rpm, the more likely the machine is to fail

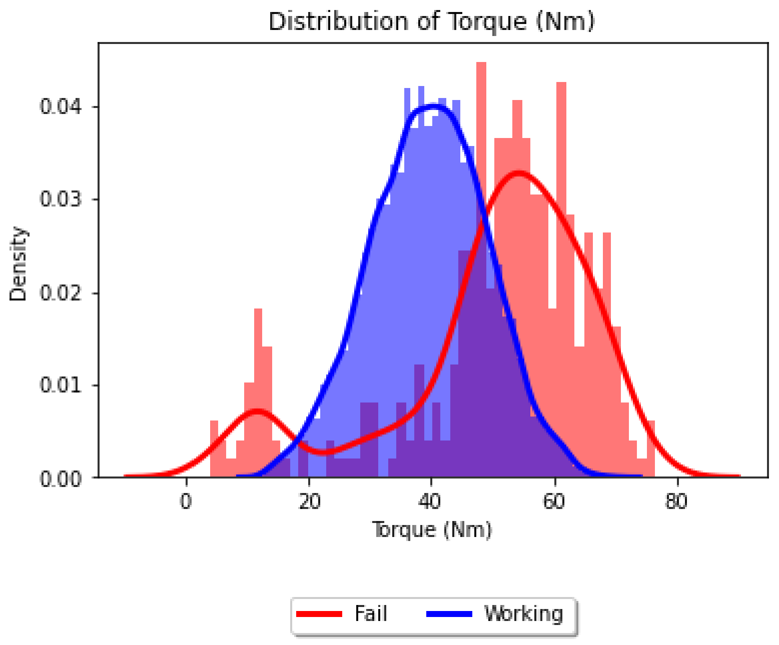
In [ ]:
```python
# Rotation Speed (rpm)
plt.hist(
    df[df["Machine Status"] == 1]["Rotation Speed (rpm)"],
    density=True,
    bins=50,
    color="#ff000088",
)
plt.hist(
    df[df["Machine Status"] == 0]["Rotation Speed (rpm)"],
    density=True,
    bins=50,
    color="#0000ff88",
)
sns.kdeplot(
    df[df["Machine Status"] == 1]["Rotation Speed (rpm)"], lw=3, color="#ff0000"
)
sns.kdeplot(
    df[df["Machine Status"] == 0]["Rotation Speed (rpm)"], lw=3, color="#0000ff"
)
plt.legend(
    np.unique(df_eda["Machine Status"]),
    loc="upper center",
    bbox_to_anchor=(0.5, -0.25),
    fancybox=True,
    shadow=True,
    ncol=3,
)
plt.title("Distribution of Rotation Speed (rpm)")
plt.show()
```



Torque (Nm)

Distribution of Torque (Nm) for machine working is normally distributed while the distribution of machine working has a bimodal distribution at around 10 and 50

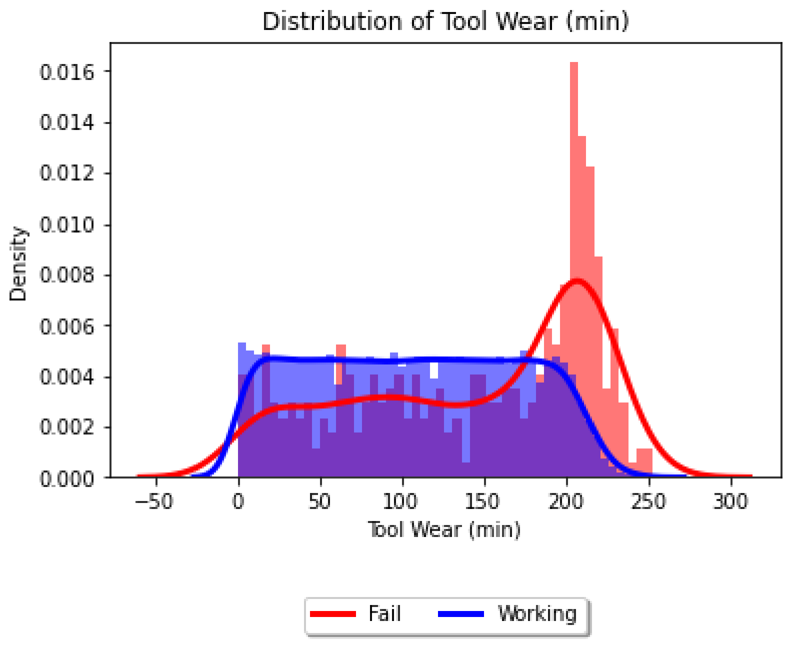
```
In [ ]: # Torque (Nm)
plt.hist(
    df[df["Machine Status"] == 1]["Torque (Nm)"],
    density=True,
    bins=50,
    color="#ff000088",
)
plt.hist(
    df[df["Machine Status"] == 0]["Torque (Nm)"],
    density=True,
    bins=50,
    color="#0000ff88",
)
sns.kdeplot(df[df["Machine Status"] == 1]["Torque (Nm)"], lw=3, color="#ff0000")
sns.kdeplot(df[df["Machine Status"] == 0]["Torque (Nm)"], lw=3, color="#0000ff")
plt.legend(
    np.unique(df_eda["Machine Status"]),
    loc="upper center",
    bbox_to_anchor=(0.5, -0.25),
    fancybox=True,
    shadow=True,
    ncol=3,
)
plt.title("Distribution of Torque (Nm)")
plt.show()
```



Tool Wear (min)

Distribution of Tool Wear (min) for working machine is relatively normal but the distribution of Tool Wear (min) for machine failure is left skewed

In [ ]:
```
# Tool Wear (min)
plt.hist(
    df[df["Machine Status"] == 1]["Tool Wear (min)"],
    density=True,
    bins=50,
    color="#ff000088",
)
plt.hist(
    df[df["Machine Status"] == 0]["Tool Wear (min)"],
    density=True,
    bins=50,
    color="#0000ff88",
)
sns.kdeplot(df[df["Machine Status"] == 1]["Tool Wear (min)"], lw=3, color="#ff0000")
sns.kdeplot(df[df["Machine Status"] == 0]["Tool Wear (min)"], lw=3, color="#0000ff")
plt.legend(
    np.unique(df_eda["Machine Status"]),
    loc="upper center",
    bbox_to_anchor=(0.5, -0.25),
    fancybox=True,
    shadow=True,
    ncol=3,
)
plt.title("Distribution of Tool Wear (min)")
plt.show()
```



Bivariate Analysis

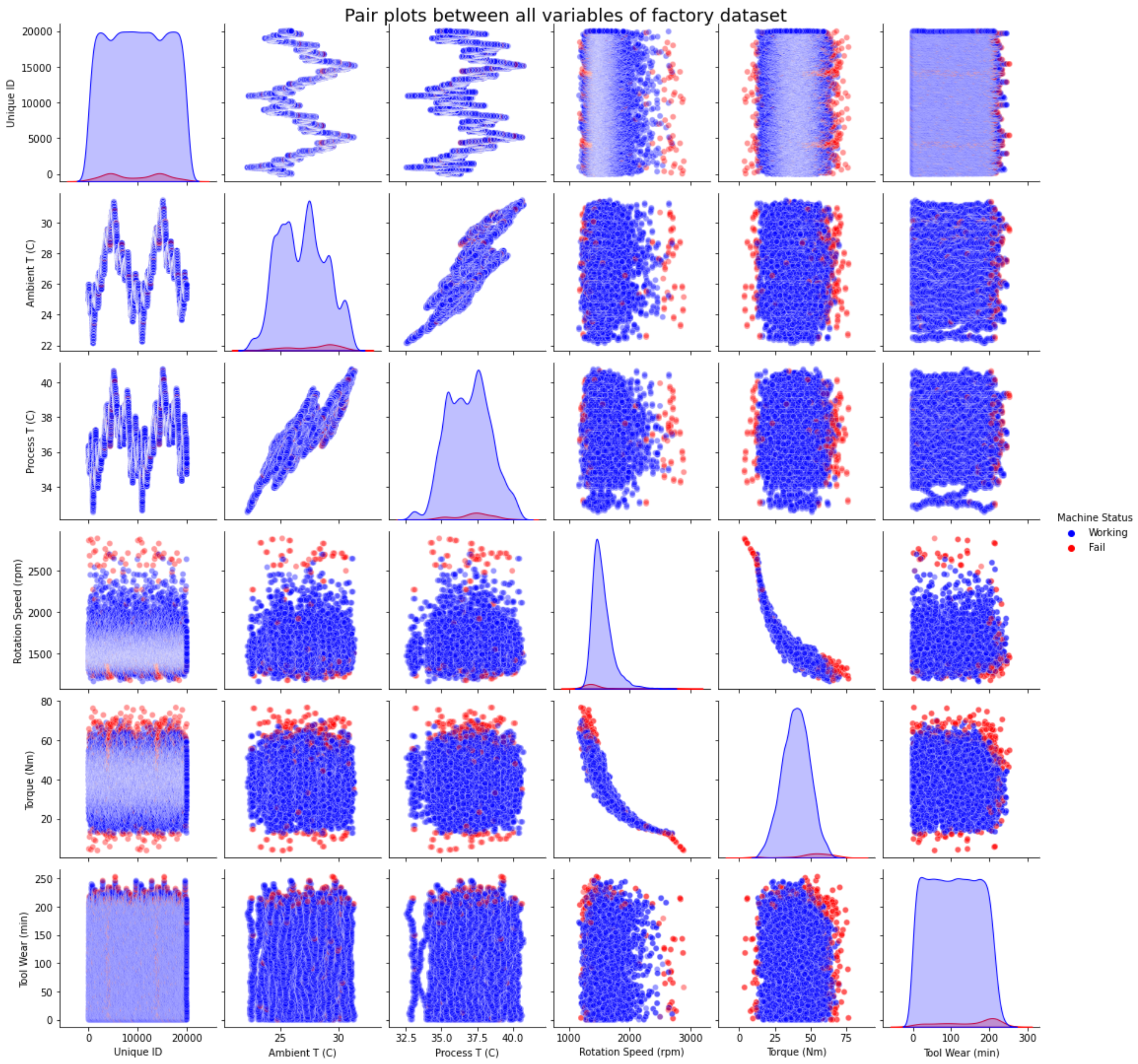
We will analysis the relationships between the different variables

Pairplot

Since our feature space is not extremely large, we can afford to plot out a Pairplot to visualise the distribution of data points with relation to Target variable Machine Status

Is there a noticable pattern relating Machine Status with Quantitave variables like Ambient T and Process T List item

In [ ]:
```
g = sns.pairplot(
    df_eda.drop(columns=["Product ID"]),
    hue="Machine Status",
    palette=["b", "r"],
    plot_kws=dict(alpha=0.4),
)
g.fig.suptitle("Pair plots between all variables of factory dataset", y=1.001, fontsize=18)
plt.show()
```



Observations

- For Rotation Speed (rpm) and Torque (Nm), there is a general downward trend
- For Ambient T (C) and Process T (C), there is a general upward trend
- There is no clear trend for other variables

Pearson's r Correlations

To check for correlation between the features and target, we will make use Pearson's r correlation coefficient. The Pearson's r correlation is able to measure the linear correlation between the two variables. Furthermore, r is invariant under separate changes in location and scale of the two variables, implying that for a linear function the angle to the x-axis does not affect r.

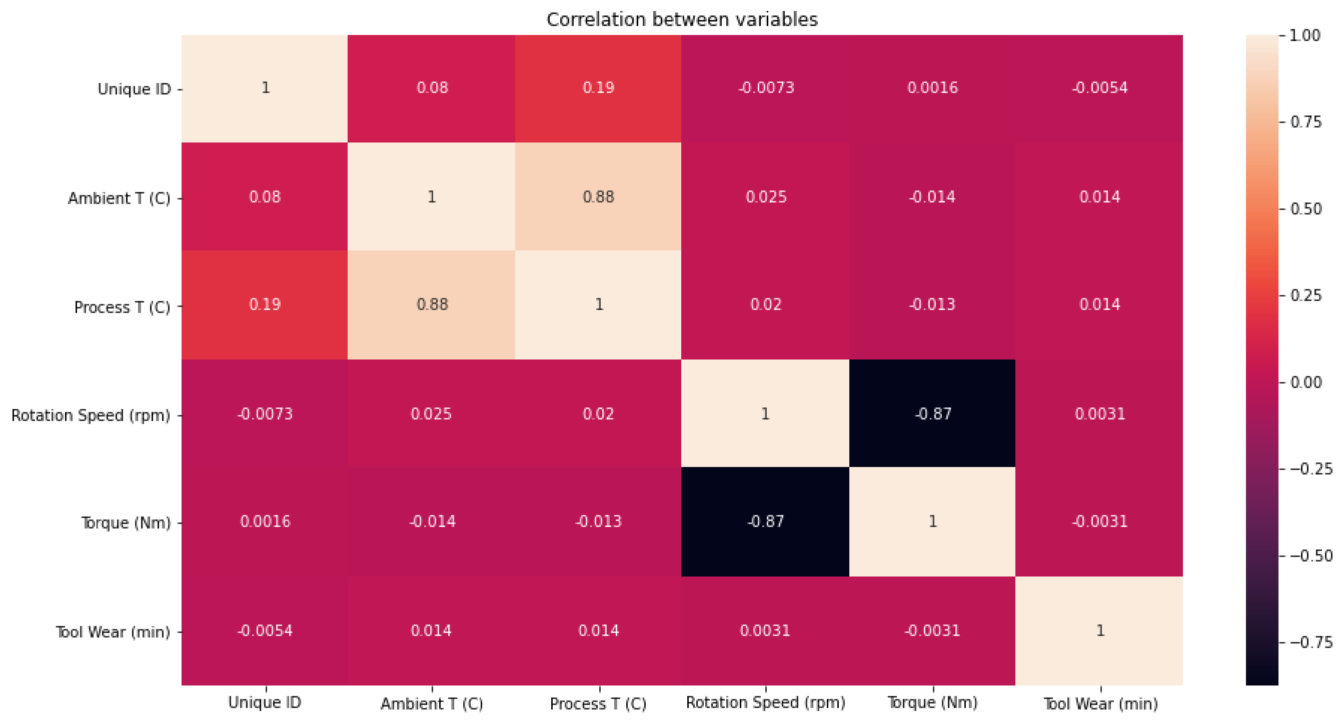
To calculate r for two variables X and Y, one divides the covariance of X and Y by the product of their standard deviations.

Formula:

$$\rho = \frac{\mathrm{cov}(X, Y)}{\sigma_x \sigma_y} \tag{1}$$

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2(y_i - \overline{y})^2}} \tag{2}$$

```
In [ ]: plt.figure(figsize=(15, 8))
        sns.heatmap(df_eda.corr(), annot=True).set(title="Correlation between variables")
        plt.show()
```



	Unique ID	Ambient T (C)	Process T (C)	Rotation Speed (rpm)	Torque (Nm)	Tool Wear (min)
Unique ID	1	0.08	0.19	-0.0073	0.0016	-0.0054
Ambient T (C)	0.08	1	0.88	0.025	-0.014	0.014
Process T (C)	0.19	0.88	1	0.02	-0.013	0.014
Rotation Speed (rpm)	-0.0073	0.025	0.02	1	-0.87	0.0031
Torque (Nm)	0.0016	-0.014	-0.013	-0.87	1	-0.0031
Tool Wear (min)	-0.0054	0.014	0.014	0.0031	-0.0031	1

Summary

- We can see that Process T (C) and Ambient T (C) has a high positive correlation value at 0.88
- We can see that Rotation Speed (rpm) and Torque (Nm) has a high negative correlation value at -0.87
- In regards to the other variables, there is no clear correlations between them

Note: However, the Pearson's r Correlation is unable to calculate the correlation between qualitative data like Quality.

Dropping Redundant Columns

Things to be done:

1. Dropping features with high cardinality (Product ID) which means that Product ID does not have any clear correlation with machine status
2. Dropping features that are unique (Unique ID) as the values are unique although there are correlation between it and Process T and Ambient T

```
In [ ]: df.drop("Product ID", axis=1, inplace=True)
        df.drop("Unique ID", axis=1, inplace=True)
```

Data Preparation

Before we can train a machine learning algorithm on our data, we first need to prepare our data.

Separate Target Label and Features

We will first separate our target label from the features. It is also necessary to perform a label encoding on the target label to convert it to a number.

```
In [ ]: X, y = df.drop("Machine Status", axis=1), df["Machine Status"]
```

Splitting Data points

To evaluate our final chosen models, we will leave a small independent test set to report on the final performance of our classifiers. When building the hold out set, we use stratify to ensure that the distribution of classes is the same in both the independent set and the training set.

```
In [ ]: X_train, X_test, y_train, y_test = train_test_split(
            X, y, test_size=0.2, stratify=y, shuffle=True, random_state=random_state
        )
        X_training = X_train.copy()
```

```
In [ ]: X_training.shape

Out[ ]: (16000, 6)
```

```
In [ ]: X_test.shape

Out[ ]: (4000, 6)
```

Data Preprocessing & Feature Engineering

As we have done the EDA of the data, we learn that we need to handle some missing values etc

Handling missing data

Using the .isna().sum() methods from Pandas, we are able to sum up the numbers of missing data per column

```
In [ ]: X_training.isna().sum()

Out[ ]: Quality                 775
        Ambient T (C)             0
        Process T (C)           318
        Rotation Speed (rpm)    915
        Torque (Nm)               0
        Tool Wear (min)           0
        dtype: int64
```

There are multiple ways to handle missing data:

1. Drop the entire column
2. Impute with Central Tendency (Mean, Mode or Median)

3. Impute with Advanced Algorithm in SKLearn (e.g. IterativeImputer, KNNImputer)

We will use the Advanced Algorithm in sklearn IterativeImputer. It will impute missing values by modelling each feature with missing values as a function of other features in a round-robin fashion.

In [ ]:
```
# All Numerical Features that has missing values
num_cols = ["Rotation Speed (rpm)", "Process T (C)"]

# initialize Imputer
imputer = IterativeImputer()
# Impute Train Data
X_training.loc[:, num_cols] = imputer.fit_transform(X_training[num_cols])
```

We will be using SimpleImputer from sklearn.impute to impute missing values with the mode value for the categorical data points.

In [ ]:
```
# All Categorical Features that has missing values
cat_cols = ["Quality"]

# initialize Imputer
imp = SimpleImputer(strategy="most_frequent")
# Impute Train Data
X_training.loc[:, cat_cols] = imp.fit_transform(X_training[cat_cols])

# Check if there are any left over na values
X_training.isna().sum()
X_training.sort_values("Ambient T (C)")
```

Out[ ]:

	Quality	Ambient T (C)	Process T (C)	Rotation Speed (rpm)	Torque (Nm)	Tool Wear (min)
918	M	22.15	36.901997	1473.000000	38.5	189
10918	M	22.25	32.650000	1473.000000	38.5	189
10916	M	22.25	32.750000	1589.000000	36.2	184
10917	L	22.25	32.650000	1475.000000	51.0	187
914	M	22.25	32.750000	1532.812429	40.6	178
...	...	...	...	...	...	...
15139	M	31.35	40.550000	1510.000000	38.9	199
5145	L	31.35	40.550000	1670.000000	32.9	7
15144	L	31.35	36.920774	1607.000000	33.5	5
15142	L	31.35	40.550000	1568.000000	39.1	0
15145	L	31.45	40.650000	1670.000000	32.9	7

16000 rows × 6 columns

Categorical Encoding

As the our dataset still contains categorical data which is hard for some of sklearn's model to train on, we have to encode the data using one of the encoders.

1. pd.get_dummies()
2. One Hot Encoder

3. Label Encoder
4. Ordinal Encoder

We choose Label Encoder in this case as pd.get_dummies() is harder to implement in a pipeline, one hot encoder is for categorical data which are nominal which Quality is not. We use Ordinal Encoder here as Label Encoder is used for target variables

```
In [ ]: enc = OrdinalEncoder(handle_unknown="use_encoded_value", unknown_value=-1)
        X_training[["Quality"]] = enc.fit_transform(X_training[["Quality"]])
        X_training
```

Out[ ]:

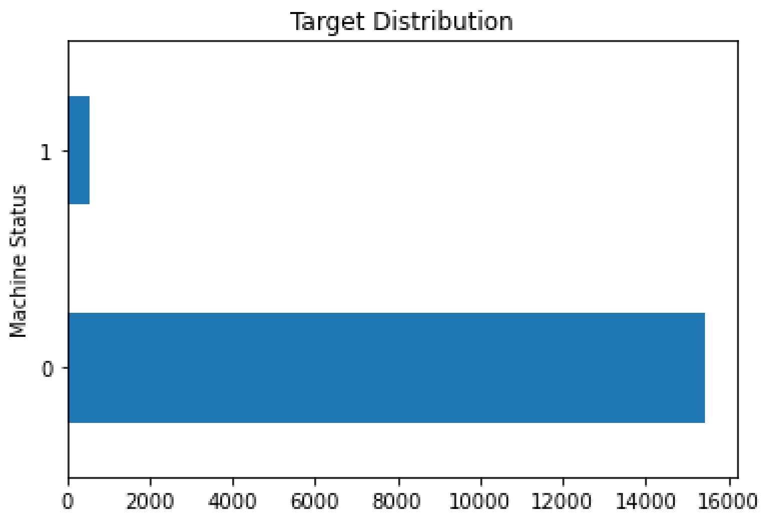
	Quality	Ambient T (C)	Process T (C)	Rotation Speed (rpm)	Torque (Nm)	Tool Wear (min)
16976	1.0	27.55	37.85	1344.000000	46.7	133
8407	1.0	25.25	36.35	1357.000000	50.1	125
2698	1.0	26.85	36.25	2010.000000	20.0	55
15263	1.0	30.45	39.75	1877.000000	22.3	96
716	0.0	24.25	35.45	1420.000000	45.8	120
...	...	...	...	...	...	...
459	1.0	24.25	35.45	1536.937399	42.3	107
6234	1.0	28.05	37.65	1479.000000	41.2	155
15586	2.0	29.35	38.75	1557.000000	31.5	49
14736	1.0	30.15	38.45	1513.000000	37.9	0
7923	2.0	27.65	38.85	1450.000000	45.0	183

16000 rows × 6 columns

Handling Imbalanced data through RESAMPLING

As mentioned before, the distribution of machine status is imbalanced, we can visualise this through plotting of the y_train values

```
In [ ]: ax = y_train.value_counts().plot(
            kind="barh",
            title="Target Distribution",
            xlabel="Machine Status",
            ylabel="Number of Machines",
        )
```



To solve this imbalanced, we can use the following solutions

1. Random Resampling
2. SMOTE (Synthetic Minority Oversampling Technique)

We will be using Random Resampling for this example. The reason is SMOTE is able to synthesize data which will affect columns like Quality which we have hot encoded.

In [ ]:
```
resample = RandomOverSampler(random_state=11)

X_resampled_train, y_resampled_train = resample.fit_resample(X_training, y_train)
X_resampled_train
```

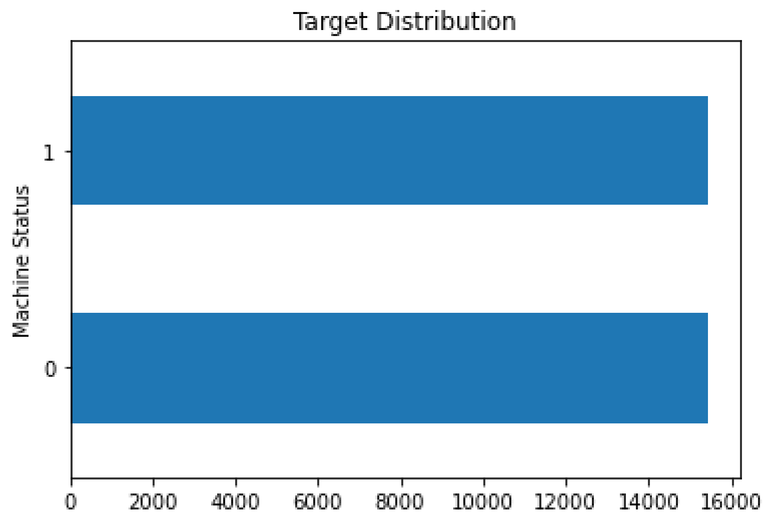
Out[ ]:

	Quality	Ambient T (C)	Process T (C)	Rotation Speed (rpm)	Torque (Nm)	Tool Wear (min)
0	1.0	27.55	37.85	1344.0	46.7	133
1	1.0	25.25	36.35	1357.0	50.1	125
2	1.0	26.85	36.25	2010.0	20.0	55
3	1.0	30.45	39.75	1877.0	22.3	96
4	0.0	24.25	35.45	1420.0	45.8	120
...	...	...	...	...	...	...
30911	2.0	29.55	37.95	1297.0	60.7	125
30912	2.0	29.55	37.95	1297.0	60.7	125
30913	1.0	26.35	37.75	1376.0	53.9	215
30914	0.0	30.55	39.15	1371.0	54.6	112
30915	1.0	28.05	37.85	1282.0	67.9	10

30916 rows × 6 columns

Let's see what happened after resampling

In [ ]:
```
ax = y_resampled_train.value_counts().plot(
    kind="barh",
    title="Target Distribution",
    xlabel="Machine Status",
    ylabel="Number of Machines",
)
```



Feature Engineering

There are certain factors which can affect machines like:

1. Temperature difference
2. High horsepower

Formulas for the factors:

Temperature Difference

$$\Delta Temp = ProcessTemp - AmbientTemp \tag{3}$$

Horsepower

$$Horsepower = Torque \times \frac{RotationSpeed}{5252} \tag{4}$$

In [ ]:
```
# Calculating Temperature Difference
X_resampled_train["Temp Diff (C)"] = (
    X_resampled_train["Process T (C)"] - X_resampled_train["Ambient T (C)"]
)


# Calculating Horsepower
X_resampled_train["Horsepower (HP)"] = (
    X_resampled_train["Torque (Nm)"] * X_resampled_train["Rotation Speed (rpm)"] / 5252
)

X_resampled_train
```

Out[ ]:

	Quality	Ambient T (C)	Process T (C)	Rotation Speed (rpm)	Torque (Nm)	Tool Wear (min)	Temp Diff (C)	Horsepower (HP)
0	1.0	27.55	37.85	1344.0	46.7	133	10.3	11.950647
1	1.0	25.25	36.35	1357.0	50.1	125	11.1	12.944726
2	1.0	26.85	36.25	2010.0	20.0	55	9.4	7.654227
3	1.0	30.45	39.75	1877.0	22.3	96	9.3	7.969745
4	0.0	24.25	35.45	1420.0	45.8	120	11.2	12.383092
...	...	...	...	...	...	...	...	...
30911	2.0	29.55	37.95	1297.0	60.7	125	8.4	14.990080
30912	2.0	29.55	37.95	1297.0	60.7	125	8.4	14.990080
30913	1.0	26.35	37.75	1376.0	53.9	215	11.4	14.121554
30914	0.0	30.55	39.15	1371.0	54.6	112	8.6	14.252970
30915	1.0	28.05	37.85	1282.0	67.9	10	9.8	16.574219

30916 rows × 8 columns

Standardization

We will be using StandardScaler as the standardize. Standard Scaler will scale the data so that the mean is 0 and standard deviation is 1 which makes it easier for the model to work.

(Note Logistic Regression and Tree Based Models are not sensitive to the magnitude of the variables and standardizing is not necessary)

In [ ]:

```python
num_col = [
    "Ambient T (C)",
    "Process T (C)",
    "Rotation Speed (rpm)",
    "Torque (Nm)",
    "Horsepower (HP)",
    "Temp Diff (C)",
]
scale = StandardScaler()

X_scale_train = X_resampled_train.copy()
X_scale_train[num_col] = scale.fit_transform(X_scale_train[num_col])
X_scale_train
```

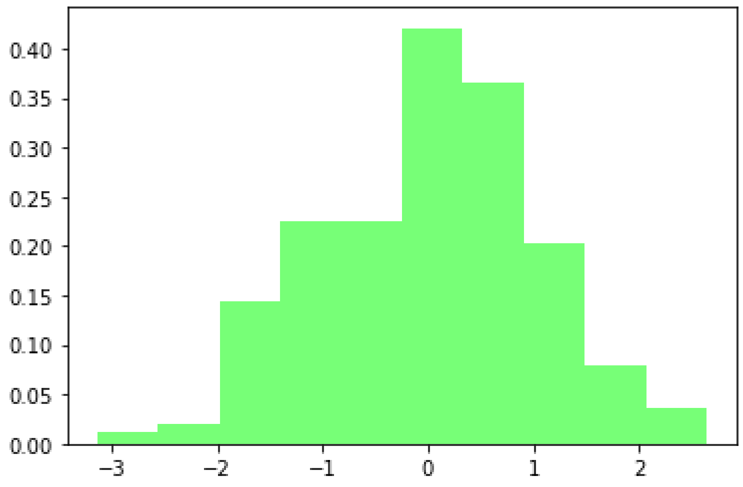
Out[ ]:

	Quality	Ambient T (C)	Process T (C)	Rotation Speed (rpm)	Torque (Nm)	Tool Wear (min)	Temp Diff (C)	Horsepower (HP)
0	1.0	0.099631	0.572520	-0.608914	0.135367	133	0.515626	-0.119779
1	1.0	-1.011896	-0.496896	-0.564689	0.370117	125	1.206723	0.212707
2	1.0	-0.238660	-0.568191	1.656773	-1.708107	55	-0.261859	-1.556790
3	1.0	1.501121	1.927115	1.204316	-1.549306	96	-0.348246	-1.451260
4	0.0	-1.495168	-1.138547	-0.350367	0.073228	120	1.293110	0.024859
...	...	...	...	...	...	...	...	...
30911	2.0	1.066175	0.643815	-0.768805	1.101983	125	-1.125730	0.896811
30912	2.0	1.066175	0.643815	-0.768805	1.101983	125	-1.125730	0.896811
30913	1.0	-0.480296	0.501226	-0.500052	0.632484	215	1.465884	0.606317
30914	0.0	1.549448	1.499348	-0.517062	0.680815	112	-0.952956	0.650272
30915	1.0	0.341267	0.572520	-0.819834	1.599100	10	0.083690	1.426653

30916 rows × 8 columns

After standardizing the data, let's see what it did to the data, we can see that the data has a mean of 0 and looks generally normal

In [ ]:
```
scaled_df = pd.concat([X_scale_train, y_resampled_train], axis=1, join="outer")
# Process T (C)
plt.hist(scaled_df["Process T (C)"], density=True, bins=10, color="#00ff0088")
plt.show()
```



Model Selection

My plan for model selection is to run the data through some models and deem the best model based on metrics and explainability.

Pipeline settings

We use pipelines to prevent data leakage.

In [ ]:
```python
def horsepower(df):
    df = pd.DataFrame(
        df,
        columns=[
            "Quality",
            "Rotation Speed (rpm)",
            "Process T (C)",
            "Ambient T (C)",
            "Torque (Nm)",
            "Tool Wear (min)",
        ],
    )
    df["Horsepower (HP)"] = df["Torque (Nm)"] * df["Rotation Speed (rpm)"] / 5252
    return df


def temp_diff(df):
    df["Temp Diff (C)"] = df["Process T (C)"] - df["Ambient T (C)"]
    return df


categorical_transformer = Pipeline(
    [
        ("imputer", SimpleImputer(strategy="most_frequent")),
        (
            "encoder",
            OrdinalEncoder(handle_unknown="use_encoded_value", unknown_value=-1),
        ),
    ]
)

numeric_transformer = Pipeline([("imputer", IterativeImputer())])

preprocessor = ColumnTransformer(
    [
        ("categorical", categorical_transformer, ["Quality"]),
        ("numeric", numeric_transformer, ["Rotation Speed (rpm)", "Process T (C)"]),
    ],
    remainder="passthrough",
)

smt = RandomOverSampler(random_state=11)

steps = [
    ("preprocessing", preprocessor),
    ("over", smt),
    ("horsepower eng", FunctionTransformer(horsepower)),
    ("temp diff eng", FunctionTransformer(temp_diff)),
    ("standardize", StandardScaler()),
    ("model"),
]
STEP_LEN = len(steps) - 1
```

Scoring Methods

We will be using the following metrics to evaluate the model

Accuracy

- We use accuracy as a scoring metric as we have balanced the data and we want to look and what is the % of correctly predicted machine status

Balanced Accuracy

- Even though we have resampled the training data, the test data is imbalanced and might lead to some difference in the %

f1 score

- Harmonic mean of recall and recall, it does not care about how many true negatives are being classified

ROC_AUC

- ROC_AUC also known as Area Under the Receiver Operating Characteristic Curve allow us to range of possibilities for observation(probability) in our classification

Recall

- We use recall as higher the recall, the lower the FN which is important in this context

In [ ]:
```
# preset scoring options
scoring_methods = ["accuracy", "balanced_accuracy", "recall", "f1", "roc_auc"]
```

Baseline model

A baseline model is simple and interpretable, easy to infer upon. I am going to use DummyClassifier as a stupid baseline to benchmark against my system later on.

stratified: generates predictions by respecting the training set's class distribution.

In [ ]:
```
steps[STEP_LEN] = ("model", DummyClassifier(strategy="uniform"))
dummy = Pipeline(steps=steps)
dummy.fit(X_train, y_train)
print(f"Baseline Accuracy Score :{dummy.score(X_test, y_test)}")
scores = cross_validate(
    dummy,
    X_train,
    y_train,
    cv=10,
    scoring=scoring_methods,
    n_jobs=4,
    return_train_score=True,
)
# displaying scores
display(
    pd.DataFrame(scores)
    .append(pd.Series(pd.DataFrame(scores).mean(), name="Mean"))
    .style.apply(
        lambda x: [
            "background-color: red; color: white" if v else "" for v in x == x.min()
        ]
    )
    .apply(
        lambda x: [
            "background-color: green; color: white" if v else "" for v in x == x.max()
        ]
    )
)
```

```
Baseline Accuracy Score :0.5005
```

	fit_time	score_time	test_accuracy	train_accuracy	test_balanced_accuracy	train_balanced_accuracy	tes
0	0.096058	0.045877	0.528750	0.503819	0.514877	0.495056	0.
1	0.100053	0.041888	0.529375	0.502083	0.533072	0.504044	0.
2	0.095067	0.044881	0.483750	0.498542	0.446912	0.510120	0.
3	0.082457	0.043882	0.499375	0.504375	0.490741	0.524015	0.
4	0.053857	0.043882	0.513750	0.500625	0.524987	0.494392	0.
5	0.047872	0.042884	0.511875	0.497361	0.497209	0.481827	0.
6	0.062832	0.044880	0.491875	0.496389	0.495796	0.510984	0.
7	0.064826	0.041888	0.521250	0.497986	0.519932	0.495003	0.
8	0.067819	0.035904	0.520000	0.499653	0.505972	0.515177	0.
9	0.062831	0.032913	0.480000	0.503264	0.546631	0.503175	0.
Mean	0.073367	0.041888	0.508000	0.500410	0.507613	0.503379	0.

Observations

- The ROC AUC score is 0.5 this means that the model is randomly selecting and predicting the points
- The model is severely under-fitted as the accuracy from the training set is very low

Checking through the different models

We import some of the important models from the sklearn model and check which model is the best using their default parameters.

We will be using accuracy, balanced_accuracy, f1, recall and roc_auc to score the models.

Learning Curves

Learning Curves is a correlation between a learner's performance on a task and the number of attempts or time required to complete the task.

Before we begin, we need to make a function for us to plot the learning curve

In [ ]:
```python
def plot_learning_curve(
    model,
    X,
    y,
    scoring,
    cv=StratifiedKFold(shuffle=True, random_state=42),
    train_sizes=np.linspace(0.1, 1.0, 10),
    ax=None,
):
    try:
        model_name = type(model[-1]).__name__
    except:
        model_name = type(model).__name__
    if ax is None:
        fig, ax = plt.subplots(figsize=(10, 8))
    train_sizes, train_scores, test_scores, fit_times, _ = learning_curve(
        model,
        X,
        y,
        cv=cv,
        n_jobs=-1,
        train_sizes=train_sizes,
        return_times=True,
        scoring=scoring,
    )
    train_scores_mean = np.mean(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)

    ax.plot(train_sizes, train_scores_mean, "o-", color="r", label="Training score")
    ax.plot(
        train_sizes, test_scores_mean, "o-", color="g", label="Cross-validation score"
    )
    ax.legend(loc="best")
    ax.set(
        ylim=(
            min(np.nanmin(train_scores), np.nanmin(test_scores)) - 0.01,
            max(np.nanmax(train_scores), np.nanmax(test_scores)) + 0.01,
        )
    )
    ax.set_title(f"Learning Curve of {model_name}")
    ax.set_ylabel(f"{scoring}")
    ax.set_xlabel("Train Sizes")
    return ax
```

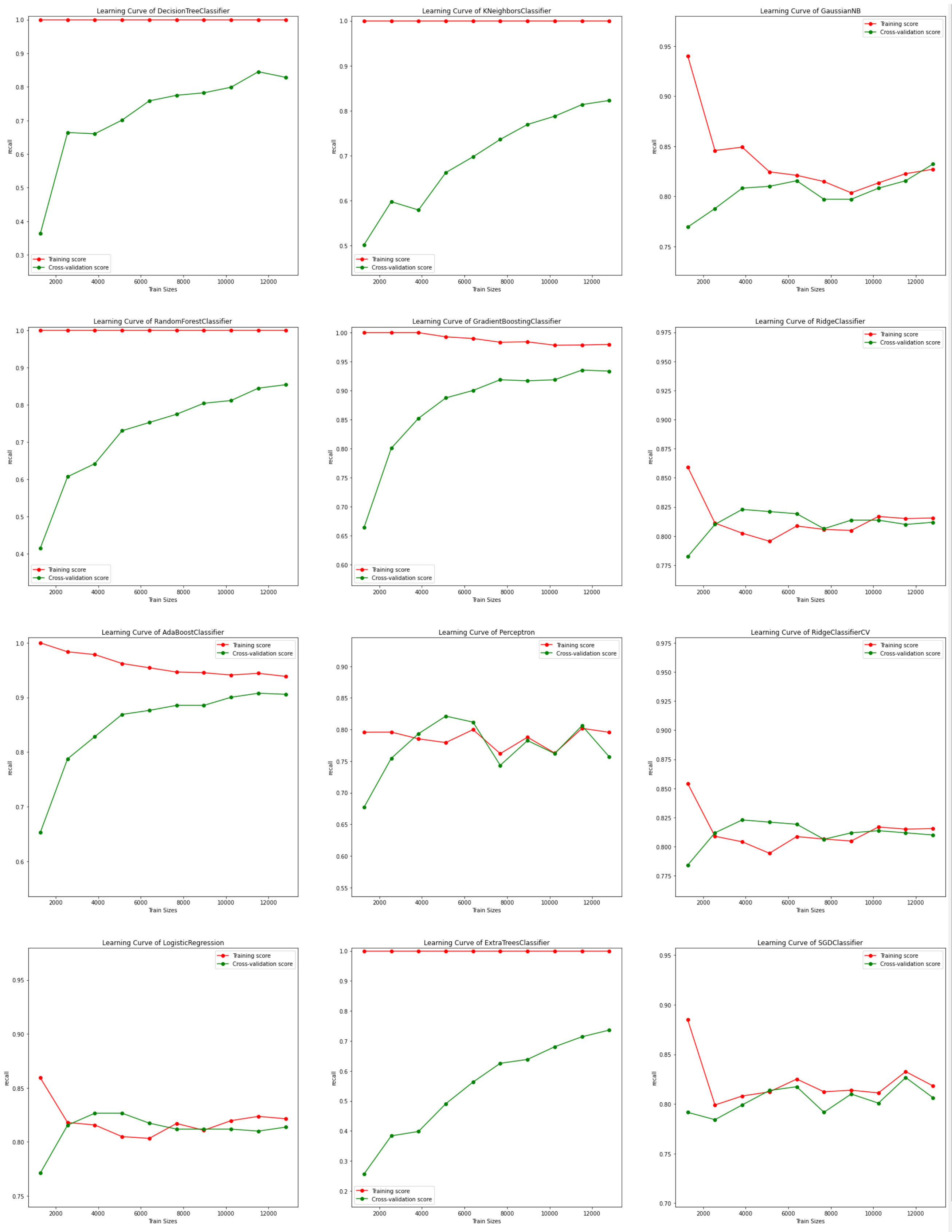
Defining models

In [ ]:
```
# Initiate Classifiers with default hyper parameters
models = [
    ("DecisionTreeClassifier", DecisionTreeClassifier()),
    ("RandomForestClassifier", RandomForestClassifier()),
    ("AdaBoostClassifier", AdaBoostClassifier()),
    ("LogisticRegression", LogisticRegression()),
    ("KNeighborsClassifier", KNeighborsClassifier()),
    ("GradientBoostingClassifier", GradientBoostingClassifier()),
    ("Perceptron", Perceptron()),
    ("ExtraTreesClassifier", ExtraTreesClassifier()),
    ("GaussianNB", GaussianNB()),
    ("RidgeClassifier", RidgeClassifier()),
    ("RidgeClassifierCV", RidgeClassifierCV()),
    ("SGDClassifier", SGDClassifier()),
]
```

In [ ]:
```
def select_model(X_train, y_train, models, scoring, ax):
    # placeholder
    out = []
    # iterate through models
    for name, model in models:
        # creating temporary pipeline
        steps[STEP_LEN] = (name, model)
        temp_pipeline = Pipeline(steps=steps)
        plot_learning_curve(
            temp_pipeline,
            X_train,
            y_train,
            scoring="recall",
            ax=ax[models.index((name, model)) % 4, models.index((name, model)) // 4],
        )
```

```python
        # cross validate
        score = cross_validate(
            temp_pipeline,
            X_train,
            y_train,
            scoring=scoring,
            n_jobs=3,
            verbose=1,
            cv=10,
            return_train_score=True,
        )
        # get the average score and then store in a Series
        out.append(pd.Series(score, name=name).apply(np.mean))
    return pd.DataFrame(out).sort_values(
        by=[
            "test_f1",
            "test_recall",
            "test_accuracy",
            "test_balanced_accuracy",
            "test_roc_auc",
        ],
        ascending=False,
    )


# Since we are comparing 12 models
fig, ax = plt.subplots(4, 3, figsize=(30, 40))

model_scores = select_model(X_train, y_train, models, scoring_methods, ax)
plt.show()
```

```
[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  10 out of  10 | elapsed:    2.7s finished
[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  10 out of  10 | elapsed:   15.5s finished
[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  10 out of  10 | elapsed:    8.0s finished
[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  10 out of  10 | elapsed:    3.4s finished
[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  10 out of  10 | elapsed:    8.9s finished
[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  10 out of  10 | elapsed:   16.6s finished
[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  10 out of  10 | elapsed:    3.0s finished
[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  10 out of  10 | elapsed:   10.6s finished
[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  10 out of  10 | elapsed:    2.9s finished
[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  10 out of  10 | elapsed:    2.9s finished
[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  10 out of  10 | elapsed:    2.9s finished
[Parallel(n_jobs=3)]: Using backend LokyBackend with 3 concurrent workers.
[Parallel(n_jobs=3)]: Done  10 out of  10 | elapsed:    3.2s finished
```



Observations

As you can see from the learning curves, the learning curve for Adaboost and Gradient Boosting when more data is fitted to the model, the cross validation score decreases.

The K Nearest Neighbour, RandomForest, ExtraTrees and DecisionTree have good learning curves are when more data is fitted to the model, the cross validation score increases and training scores remains constant. This shows that the model are becoming more generalised

In [ ]:
```
model_scores.style.apply(
    lambda x: ["background-color: red; color: white" if v else "" for v in x == x.min()]
).apply(
    lambda x: [
        "background-color: green; color: white" if v else "" for v in x == x.max()
    ]
)
```

Out[ ]:

	fit_time	score_time	test_accuracy	train_accuracy	test_balanced_accuracy	train_ba
RandomForestClassifier	2.769180	0.124666	0.994875	0.999993	0.943109	
ExtraTreesClassifier	1.487705	0.144115	0.992500	1.000000	0.895649	
DecisionTreeClassifier	0.164707	0.038597	0.991250	1.000000	0.924255	
KNeighborsClassifier	0.164795	0.218288	0.971687	0.984944	0.913237	
GradientBoostingClassifier	3.679325	0.035223	0.954500	0.957701	0.945261	
AdaBoostClassifier	1.191534	0.070356	0.936937	0.939854	0.924640	
SGDClassifier	0.205749	0.042787	0.856250	0.855417	0.838386	
RidgeClassifierCV	0.115091	0.048271	0.855937	0.856590	0.834668	
RidgeClassifier	0.091454	0.045877	0.855813	0.856563	0.834604	
GaussianNB	0.083975	0.045678	0.851313	0.852201	0.835917	
LogisticRegression	0.137047	0.042090	0.849000	0.849944	0.834619	
Perceptron	0.120599	0.047552	0.770375	0.774819	0.782259	

Observations

- Some models performs equally well with 100% mean cross-validation accuracy score of 5 folds, highlighted in green.
- Perceptron is the worst performing model because there is no clear separation for the perceptron model to divide as seen in the pairplot.

Selection of model

Therefore, we will use the RandomForestClassifier. Not only does it have one of the best accuracy. However f1 is more important than accuracy in comparing between models. The RandomForestClassifier has the highest f1 score for both test_f1 and train_f1. Therefore we will be using the RandomForestClassifier. We will also test the DecisionTreeClassifier as our other option and do another comparison. The reason being that DecisionTree is one of the more explainable models with a quick fit time, high f1 score and high accuracy.

Initializing RandomForestClassifier

In [ ]:
```
steps[STEP_LEN] = ("model", RandomForestClassifier())

tree_clf = Pipeline(steps=steps)
tree_clf.fit(X_train, y_train)
print(f"Model Accuracy Score :{tree_clf.score(X_train, y_train)}")
scores = cross_validate(
    tree_clf,
    X_train,
    y_train,
    cv=10,
    scoring=scoring_methods,
    n_jobs=4,
    return_train_score=True,
)
# displaying scores
display(
    pd.DataFrame(scores)
    .append(pd.Series(pd.DataFrame(scores).mean(), name="Mean"))
    .style.apply(
        lambda x: [
            "background-color: red; color: white" if v else "" for v in x == x.min()
        ]
    )
    .apply(
        lambda x: [
            "background-color: green; color: white" if v else "" for v in x == x.max()
        ]
    )
)
```

```
Model Accuracy Score :1.0
```

	fit_time	score_time	test_accuracy	train_accuracy	test_balanced_accuracy	train_balanced_accuracy	tes
0	2.932159	0.150599	0.995000	1.000000	0.934862	1.000000	0.
1	2.921188	0.149601	0.996250	1.000000	0.944444	1.000000	0.
2	2.942132	0.148603	0.993125	1.000000	0.942827	1.000000	0.
3	2.896255	0.146607	0.996250	1.000000	0.962316	1.000000	0.
4	2.575112	0.140623	0.994375	1.000000	0.925603	1.000000	0.
5	2.566140	0.153591	0.996250	1.000000	0.962316	1.000000	0.
6	2.622987	0.133643	0.993125	1.000000	0.924956	1.000000	0.
7	2.623985	0.139627	0.995000	1.000000	0.943798	1.000000	0.
8	1.901914	0.070810	0.993125	1.000000	0.926302	1.000000	0.
9	1.911866	0.070810	0.993750	1.000000	0.935393	1.000000	0.
Mean	2.589374	0.130451	0.994625	1.000000	0.940282	1.000000	0.

Observations

- 10 fold cross validation shows that the model is strong at predicting based on the high test accuracy, test f1 score

Initializing DecisionTreeClassifier

```
In [ ]: steps[STEP_LEN] = ("model", DecisionTreeClassifier())

        d_tree_clf = Pipeline(steps=steps)
        d_tree_clf.fit(X_train, y_train)
        print(f"Model Accuracy Score :{d_tree_clf.score(X_train, y_train)}")
        scores = cross_validate(
            d_tree_clf,
            X_train,
            y_train,
            cv=10,
            scoring=scoring_methods,
            n_jobs=4,
            return_train_score=True,
        )
        # displaying scores
        display(
            pd.DataFrame(scores)
            .append(pd.Series(pd.DataFrame(scores).mean(), name="Mean"))
            .style.apply(
                lambda x: [
                    "background-color: red; color: white" if v else "" for v in x == x.min()
                ]
            )
            .apply(
                lambda x: [
                    "background-color: green; color: white" if v else "" for v in x == x.max()
                ]
            )
        )
```

```
Model Accuracy Score :1.0
```

	fit_time	score_time	test_accuracy	train_accuracy	test_balanced_accuracy	train_balanced_accuracy	tes
0	0.194480	0.048870	0.991875	1.000000	0.915373	1.000000	0.
1	0.189487	0.044880	0.987500	1.000000	0.904173	1.000000	0.
2	0.193481	0.045878	0.990000	1.000000	0.923339	1.000000	0.
3	0.190490	0.046877	0.991250	1.000000	0.941857	1.000000	0.
4	0.184506	0.049868	0.991875	1.000000	0.924309	1.000000	0.
5	0.186499	0.048870	0.992500	1.000000	0.969311	1.000000	0.
6	0.193480	0.048870	0.990625	1.000000	0.905790	1.000000	0.
7	0.208440	0.044880	0.992500	1.000000	0.933568	1.000000	0.
8	0.157578	0.034906	0.991250	1.000000	0.907796	1.000000	0.
9	0.160568	0.035904	0.993750	1.000000	0.926625	1.000000	0.
Mean	0.185901	0.044980	0.991312	1.000000	0.925214	1.000000	0.

Observations

- 10 fold cross validation shows that the model is strong at predicting based on the high test accuracy and high test f1 score

Comparing models with baseline

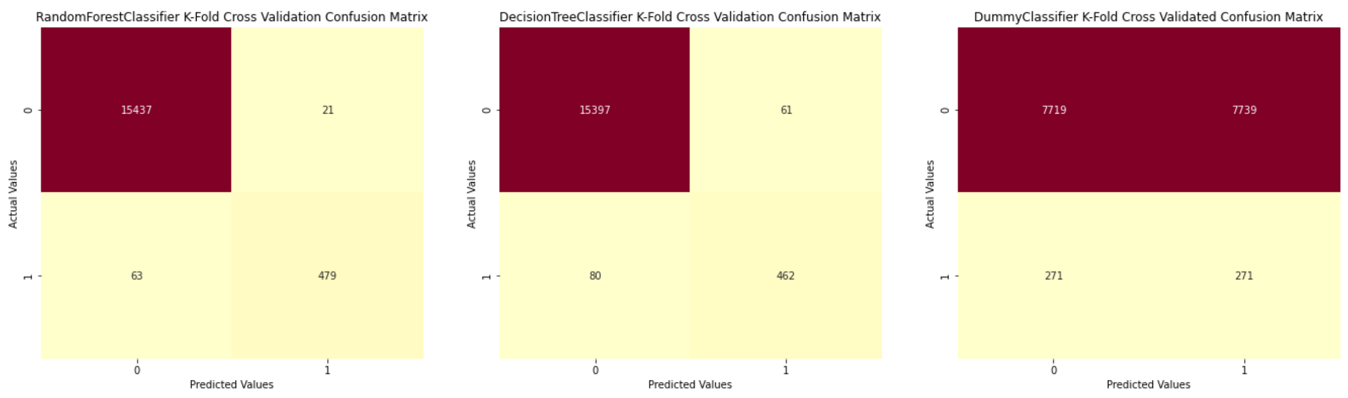
To compare the RandomForestClassifier and Baseline model and DecisionTreeClassifier, we will use the following attributes.

1. Confusion Matrix
2. Learning Curve

Confusion Matrix

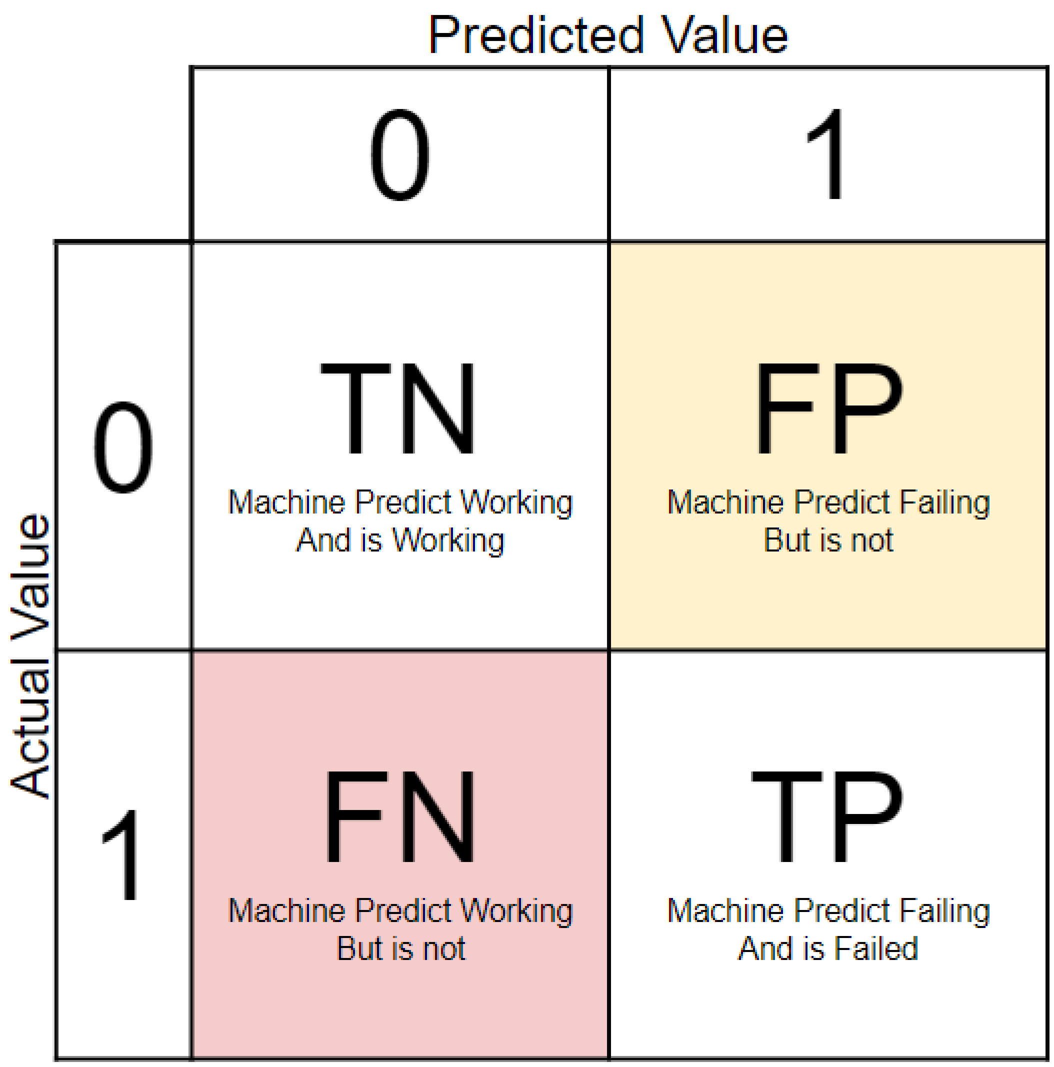
A confusion matrix is a table that is often used to describe the performance of a classifier on a set of test data for which the true values are known.

In [ ]:
```python
# Cross Validating Confusion Matrix
fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(23, 6))
# RandomForestClassifier
tree_cm = confusion_matrix(
    y_train, cross_val_predict(tree_clf, X_train, y_train, cv=10)
)
sns.heatmap(tree_cm, annot=True, fmt="", ax=ax1, cbar=False, cmap="YlOrRd")
ax1.set_title("RandomForestClassifier K-Fold Cross Validation Confusion Matrix")
ax1.set_ylabel("Actual Values")
ax1.set_xlabel("Predicted Values")

# DecisionTreeClassifier
d_tree_cm = confusion_matrix(
    y_train, cross_val_predict(d_tree_clf, X_train, y_train, cv=10)
)
sns.heatmap(d_tree_cm, annot=True, fmt="", ax=ax2, cbar=False, cmap="YlOrRd")
ax2.set_title("DecisionTreeClassifier K-Fold Cross Validation Confusion Matrix")
ax2.set_ylabel("Actual Values")
ax2.set_xlabel("Predicted Values")

# Baseline
dummy_cm = confusion_matrix(y_train, cross_val_predict(dummy, X_train, y_train, cv=10))
sns.heatmap(dummy_cm, annot=True, fmt="", ax=ax3, cbar=False, cmap="YlOrRd")
ax3.set_title("DummyClassifier K-Fold Cross Validated Confusion Matrix")
ax3.set_ylabel("Actual Values")
ax3.set_xlabel("Predicted Values")

plt.show()
```



How Confusion Matrix Works in this context?

The following image is created using Google Slides:


Predicted Value
0
1
Actual Value
0
1
TN
Machine Predict Working And is Working
FP
Machine Predict Failing But is not
FN
Machine Predict Working But is not
TP
Machine Predict Failing And is Failed

Legend:
FN => False Negative
TN => True Negative
FP => False Positive
TP => True Positive

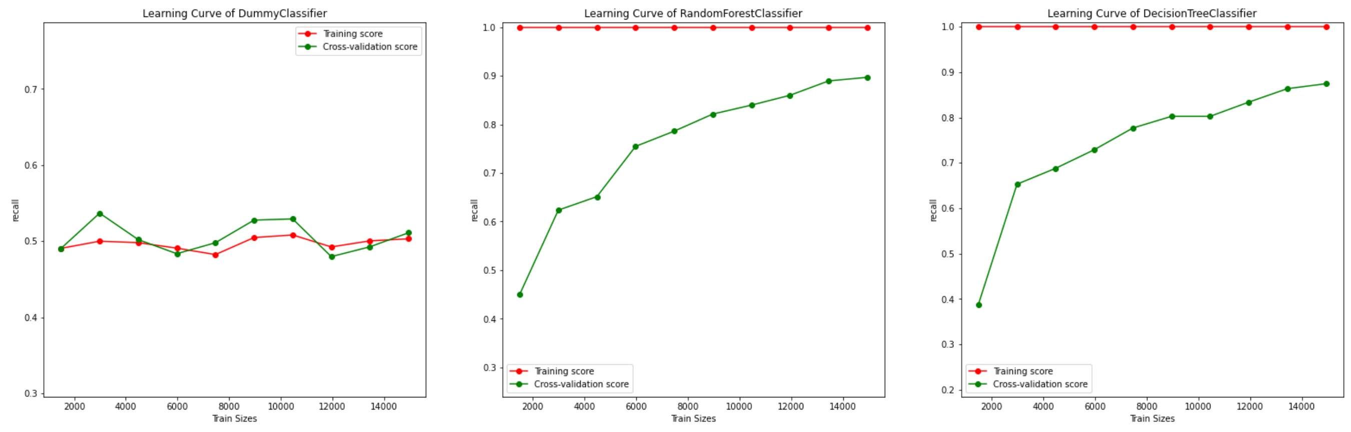
In this case, we want to reduce FP as we do not want to get maintenance for a machine which is actually working perfectly and we also want to reduce FN as the machine has failed and it is predicted to be working can cause a halt in production.

**Therefore, FN is more important and needs to be smaller than FP

Observations

- Baseline model's predictions are all over the place
- RandomForestClassifier model predictions for FN is 68 and FP is 20 (Close To 0 based %). This means that the model is able to help us predict with minor errors.
- DecisionTreeClassifier model predictions for FN is 77 and FP is 61 (Close To 0 based %). This means that the model is able to help us predict with minor errors.

In [ ]:
```
fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(27, 8))
plot_learning_curve(dummy, X_train, y_train, scoring="recall", cv=15, ax=ax1)
plot_learning_curve(tree_clf, X_train, y_train, scoring="recall", cv=15, ax=ax2)
plot_learning_curve(d_tree_clf, X_train, y_train, scoring="recall", cv=15, ax=ax3)
plt.show()
```



Observations

- Learning Curve for DummyClassifier is very random and is unrepresentative. This shows that the model is severely under-fitted
- Learning Curve of RandomForestClassifier and DecisionTreeClassifier is increases and becomes more generalised as more data is added
- However, the f1 curve of RandomForestClassifier has a higher end point compared to the DecisionTreeClassifier which can suggest that RandomForestClassifier is a better model

Generating predictions

we want to see how the model fair against unseen data

In [ ]:
```
tree_y_pred = tree_clf.predict(X_test)
d_tree_y_pred = d_tree_clf.predict(X_test)
# Classification Report
print(
    f"""
RandomForestClassifier:
{classification_report(y_test, tree_y_pred, digits=3)}

DecisionTreeClassifier:
{classification_report(y_test, d_tree_y_pred, digits=3)}
"""
)
```

```
RandomForestClassifier:
              precision    recall  f1-score   support

           0      0.996     1.000     0.998      3864
           1      0.992     0.875     0.930       136

    accuracy                          0.996      4000
   macro avg      0.994     0.937     0.964      4000
weighted avg      0.995     0.996     0.995      4000


DecisionTreeClassifier:
              precision    recall  f1-score   support

           0      0.995     0.997     0.996      3864
           1      0.913     0.846     0.878       136

    accuracy                          0.992      4000
   macro avg      0.954     0.921     0.937      4000
weighted avg      0.992     0.992     0.992      4000
```

Observations

- By comparing f1 scores, RandomForestClassifier is better as the f1 score for RandomForestClassifier(0.930) is higher than f1 score for DecisionTreeClassifier(0.862)
- As explained in the confusion matrix section, RandomForestClassifier is once again better due to the higher recall score for RandomForestClassifier(0.875) compared to DecisionTreeClassifier(0.824)
- In terms of accuracy, RandomForestClassifier is slightly higher than DecisionTreeClassifier at 0.996 and 0.991 respectively
- However, more improvement can be done to the model to make it better

Model Improvement

Although our models perform very well, there are still some improvements to be made to our models by simplifying them to make them more generalizable. Let's see what are the possible params that can be tuned.

```
In [ ]: list(RandomForestClassifier().get_params().keys())
```

```
Out[ ]: ['bootstrap',
         'ccp_alpha',
         'class_weight',
         'criterion',
         'max_depth',
         'max_features',
         'max_leaf_nodes',
         'max_samples',
         'min_impurity_decrease',
         'min_samples_leaf',
         'min_samples_split',
         'min_weight_fraction_leaf',
         'n_estimators',
         'n_jobs',
         'oob_score',
         'random_state',
         'verbose',
         'warm_start']
```

```
In [ ]: list(DecisionTreeClassifier().get_params().keys())
```

```
Out[ ]: ['ccp_alpha',
         'class_weight',
         'criterion',
         'max_depth',
         'max_features',
         'max_leaf_nodes',
         'min_impurity_decrease',
         'min_samples_leaf',
         'min_samples_split',
         'min_weight_fraction_leaf',
         'random_state',
         'splitter']
```

Hyperparameter Tuning and Evaluation

We will be using RandomizedSearchCV to run through the parameters to see which model's parameter will give the best f1 score.

Parameters to be tuned (RandomForestClassifier):

1. max_depth - maximum depth of the tree, basically how big can the tree grow
2. max_leaf_nodes - stopping criteria for number of leaves
3. n_estimators - The number of trees in the forest

Parameters to be tuned (DecisionTreeClassifier):

1. max_depth - maximum depth of the tree, basically how big can the tree grow
2. max_leaf_nodes - stopping criteria for number of leaves

RandomizedSearchCV

The only difference between both the approaches is in grid search we define the combinations and do training of the model whereas in RandomizedSearchCV the model selects the combinations randomly. This means that generally RandomizedSearchCV will be faster than GridSearchCV. GridSearchCV will find the best values based on scoring metrics by training however, RandomizedSearchCV will choose n_iter (default=10) and compare to see which of the following gives the best metrics

In [ ]:
```
# Create the parameter grid
params_grid = {
    "max_depth": [5,10,20,30,40,50,60,70,80,90,100],
    "max_leaf_nodes": np.arange(10, 16),
    "n_estimators": [100, 500, 1000],
}

# Creating a model based on the pipeline
steps[STEP_LEN] = (
    "hyper",
    RandomizedSearchCV(
        RandomForestClassifier(
            min_samples_split=2, min_samples_leaf=1, criterion="entropy"
        ),
        params_grid,
        cv=15,
        verbose=1,
        n_jobs=-1,
        scoring="f1",
        n_iter=50,
        random_state=22,
    ),
)

tree_random_search = Pipeline(steps=steps)
# Fitting Model
tree_random_search.fit(X_train, y_train)

print(tree_random_search.named_steps["hyper"].best_estimator_)
print(tree_random_search.named_steps["hyper"].best_params_)
print(tree_random_search.named_steps["hyper"].best_score_)
```

```
Fitting 15 folds for each of 50 candidates, totalling 750 fits
RandomForestClassifier(criterion='entropy', max_depth=5, max_leaf_nodes=14,
                       n_estimators=500)
{'n_estimators': 500, 'max_leaf_nodes': 14, 'max_depth': 5}
0.9458790778637244
```

In [ ]:
```
# Create the parameter grid
params_grid = {"max_depth": [5,10,20,30,40,50,60,70,80,90,100], "max_leaf_nodes": np.arange(1

# Creating a model based on the pipeline
steps[STEP_LEN] = (
    "hyper",
    RandomizedSearchCV(
        DecisionTreeClassifier(
            min_samples_split=2, min_samples_leaf=1, criterion="entropy"
        ),
        params_grid,
        cv=15,
        verbose=1,
        n_jobs=-1,
        scoring="f1",
        n_iter=50,
        random_state=22,
    ),
)

d_tree_random_search = Pipeline(steps=steps)
# Fitting Model
d_tree_random_search.fit(X_train, y_train)
print(d_tree_random_search.named_steps["hyper"].best_estimator_)
print(d_tree_random_search.named_steps["hyper"].best_params_)
print(d_tree_random_search.named_steps["hyper"].best_score_)
```

```
Fitting 15 folds for each of 50 candidates, totalling 750 fits
DecisionTreeClassifier(criterion='entropy', max_depth=5, max_leaf_nodes=15)
{'max_leaf_nodes': 15, 'max_depth': 5}
0.9484652590960423
```

Model Evaluation

We will evaluate the model on an independent test set to see if the model is able to generalize to unseen examples

In [ ]:
```
y_test.shape
```

Out[ ]:
```
(4000,)
```

There are 4000 unseen test examples

Initiate model after hyperparameter training

After training, we will have the model which will perform the best. Let's see if there is a boost in results after training

In [ ]:
```
steps[STEP_LEN] = (
    "model",
    tree_random_search.named_steps["hyper"].best_estimator_,
)

tuned_tree_clf = Pipeline(steps=steps)
# Fitting Model
tuned_tree_clf.fit(X_train, y_train)
# Creating predictions
tree_y_pred = tuned_tree_clf.predict(X_test)
```

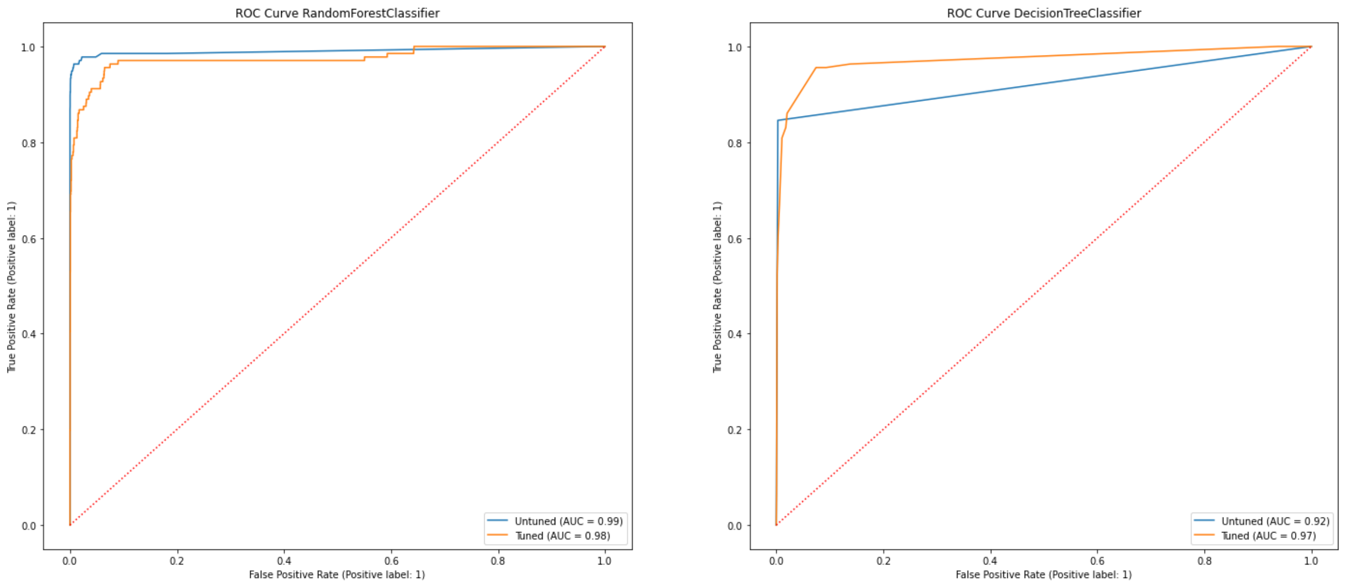
In [ ]:
```
steps[STEP_LEN] = (
    "model",
    d_tree_random_search.named_steps["hyper"].best_estimator_,
)

tuned_d_tree_clf = Pipeline(steps=steps)
# Fitting Model
tuned_d_tree_clf.fit(X_train, y_train)
# Creating predictions
d_tree_y_pred = tuned_d_tree_clf.predict(X_test)
```

Comparing RandomForestClassifier and DecisionTreeClassifier

ROC Curve

In [ ]:
```
fig, ax = plt.subplots(1, 2, figsize=(24, 10))
# RandomForestClassifier
RocCurveDisplay.from_estimator(tree_clf, X_test, y_test, ax=ax[0], name="Untuned")
RocCurveDisplay.from_estimator(tuned_tree_clf, X_test, y_test, ax=ax[0], name="Tuned")

# DecisionTreeClassifier
RocCurveDisplay.from_estimator(d_tree_clf, X_test, y_test, ax=ax[1], name="Untuned")
RocCurveDisplay.from_estimator(tuned_d_tree_clf, X_test, y_test, ax=ax[1], name="Tuned")
```

```
# 50% line
x = np.linspace(0, 1, 2)
ax[0].plot(x, x, ":", color="red")
ax[1].plot(x, x, ":", color="red")

ax[0].set_title("ROC Curve RandomForestClassifier")
ax[1].set_title("ROC Curve DecisionTreeClassifier")
plt.show()
```



Observations

We can see that the Untuned RandomForestClassifier has a higher Area Under ROC Curve (AUC) compared to the Tuned RandomForestClassifier this is because of the Max Depth Parameter that we have tuned. Compared to DecisionTreeClassifier, the Tuned DecisionTreeClassifier has a higher AUC than Untuned DecisionTreeClassifier. AUC for the Tuned RandomForestClassifier is slightly higher at 0.98 while Tuned DecisionTreeClassifier is 0.97. This means that RandomForestClassifier is better performance at distinguishing between machine status compared to DecisionTreeClassifier

In [ ]:
```
# Classification Report
print(
    f"""
RandomForestClassifier:
{classification_report(y_test, tree_y_pred, digits=3)}

DecisionTreeClassifier:
{classification_report(y_test, d_tree_y_pred, digits=3)}
"""
)
```

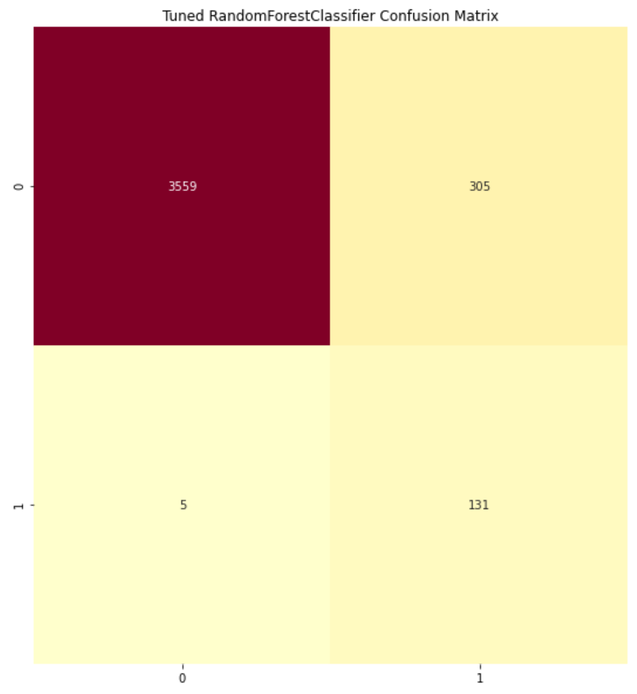
```
RandomForestClassifier:
              precision    recall  f1-score   support

           0      0.999     0.921     0.958      3864
           1      0.300     0.963     0.458       136

    accuracy                          0.922      4000
   macro avg      0.650     0.942     0.708      4000
weighted avg      0.975     0.922     0.941      4000


DecisionTreeClassifier:
              precision    recall  f1-score   support

           0      0.998     0.923     0.959      3864
           1      0.303     0.956     0.460       136

    accuracy                          0.924      4000
   macro avg      0.651     0.939     0.710      4000
weighted avg      0.975     0.924     0.942      4000
```

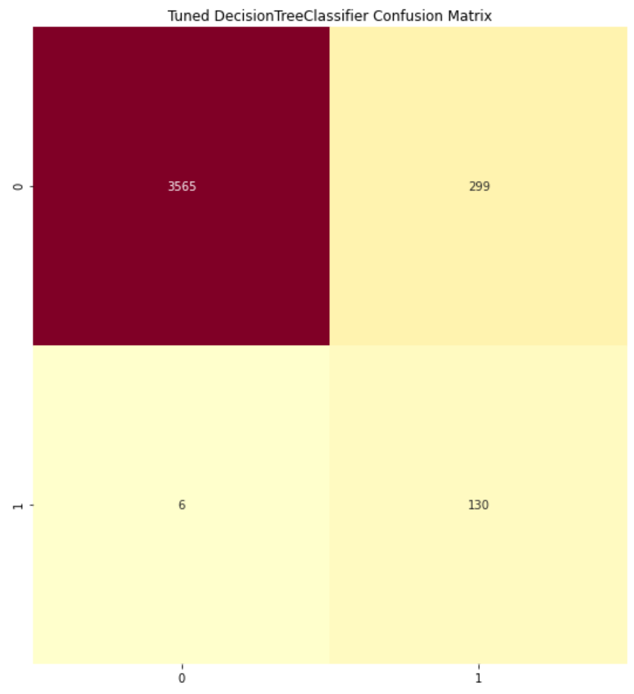
Observations

From our quick classification report, we can see that both models are quite accurate in predicting whether the machine will fail or continue working as the accuracy of both RandomForestClassifier and DecisionTreeClassifier have accuracy that is more than 0.9. If you are wondering why the untuned model has higher overall score as during our hyperparameter tuning, we limited the tree to be able to have a max depth of [5,10,20,30,40,50,60,70,80,90,100] as we do not want to make models overfit as DecisionTrees are known for overfitting. Therefore, there is a decline in overall score.

We can also see that generally, DecisionTree is able to predict with better precision, f1 score and higher accuracy. As concluded above, f1 score is the metrics to compare models and therefore DecisionTreeClassifier is a better model compared to RandomForestClassifier

In [ ]:
```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 10))
# Confusion Matrix
tree_tuned_cm = confusion_matrix(y_test, tree_y_pred)
d_tree_tuned_cm = confusion_matrix(y_test, d_tree_y_pred)
plt.figure(figsize=(10, 10))
sns.heatmap(tree_tuned_cm, annot=True, fmt="", cbar=False, cmap="YlOrRd", ax=ax1)
ax1.set_title("Tuned RandomForestClassifier Confusion Matrix")
sns.heatmap(d_tree_tuned_cm, annot=True, fmt="", cbar=False, cmap="YlOrRd", ax=ax2)
ax2.set_title("Tuned DecisionTreeClassifier Confusion Matrix")
plt.show()
```



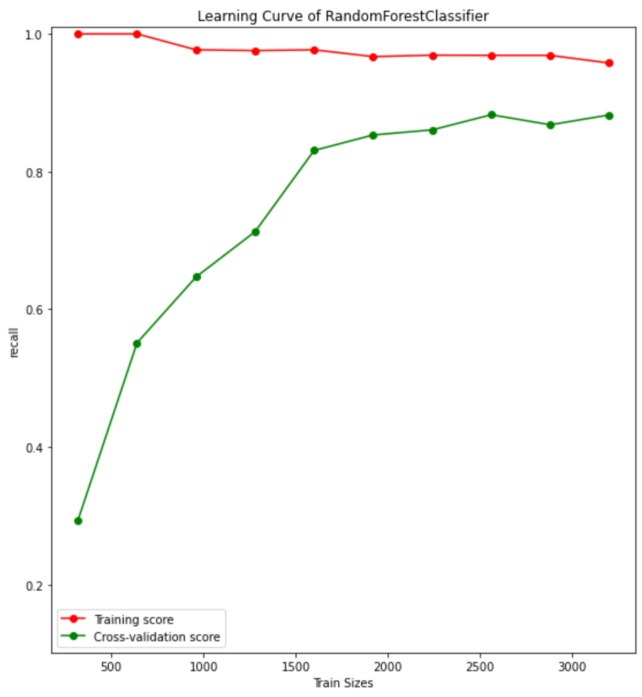


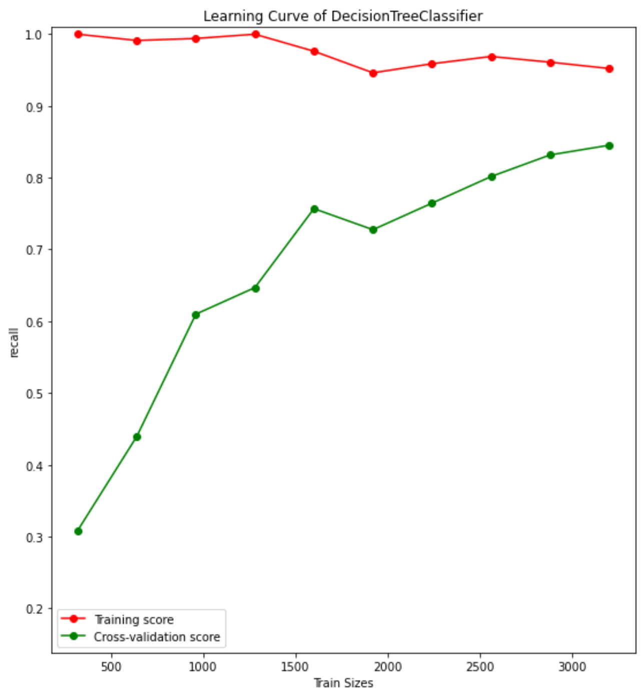
```
<Figure size 720x720 with 0 Axes>
```

Observations

We can see that our model is able to predict the machine status with high recall as the FN value is 5 and 6 for RandomForest . However, we can see that for DecisionTreeClassifier, it is able to reduce value of FP at 299 compared to RandomForestClassifier at 305.

In [ ]:
```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 10))
plot_learning_curve(tuned_tree_clf, X_test, y_test, scoring="recall", ax=ax1)
plot_learning_curve(tuned_d_tree_clf, X_test, y_test, scoring="recall", ax=ax2)
plt.show()
```





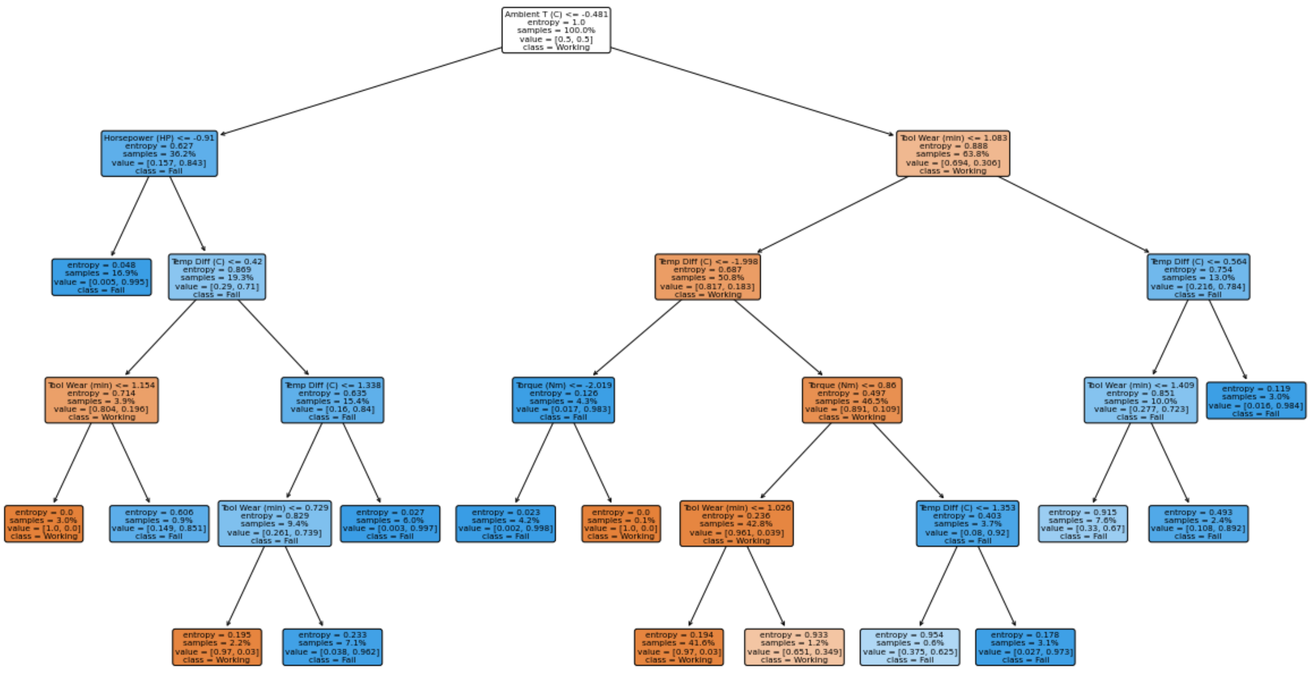
Observations

Saving model

To save, we will be using the pickle library

```
In [ ]: pickle.dump(tuned_tree_clf, open("random_forest_classifier.p", "wb"))
        tuned_tree_clf = pickle.load(open("random_forest_classifier.p", "rb"))
```

```
In [ ]: fig, ax = plt.subplots(figsize=(21, 12))
        plot_tree(tuned_d_tree_clf[-1], filled=True, ax=ax, feature_names=X_scale_train.columns,
                  class_names=["Working", "Fail"],  proportion=True, rounded=True)

        plt.show()
```



Ambient T (C) <= -0.481 entropy = 1.0 samples = 100.0% value = [0.5, 0.5] class = Working
Horsepower (HP) <= -0.91 entropy = 0.627 samples = 36.2% value = [0.157, 0.843] class = Fail
Tool Wear (min) <= 1.083 entropy = 0.888 samples = 63.8% value = [0.694, 0.306] class = Working
entropy = 0.048 samples = 16.9% value = [0.005, 0.995] class = Fail
Temp Diff (C) <= 0.42 entropy = 0.869 samples = 19.3% value = [0.29, 0.71] class = Fail
Temp Diff (C) <= -1.998 entropy = 0.687 samples = 50.8% value = [0.817, 0.183] class = Working
Temp Diff (C) <= 0.564 entropy = 0.754 samples = 13.0% value = [0.216, 0.784] class = Fail
Tool Wear (min) <= 1.154 entropy = 0.714 samples = 3.9% value = [0.804, 0.196] class = Working
Temp Diff (C) <= 1.338 entropy = 0.635 samples = 15.4% value = [0.16, 0.84] class = Fail
Torque (Nm) <= -2.019 entropy = 0.126 samples = 4.3% value = [0.017, 0.983] class = Fail
Torque (Nm) <= 0.86 entropy = 0.497 samples = 46.5% value = [0.891, 0.109] class = Working
Tool Wear (min) <= 1.409 entropy = 0.851 samples = 10.0% value = [0.277, 0.723] class = Fail
entropy = 0.119 samples = 3.0% value = [0.016, 0.984] class = Fail
entropy = 0.0 samples = 3.0% value = [1.0, 0.0] class = Working
entropy = 0.606 samples = 0.9% value = [0.149, 0.851] class = Fail
Tool Wear (min) <= 0.729 entropy = 0.829 samples = 9.4% value = [0.261, 0.739] class = Fail
entropy = 0.027 samples = 6.0% value = [0.003, 0.997] class = Fail
entropy = 0.023 samples = 4.2% value = [0.002, 0.998] class = Fail
entropy = 0.0 samples = 0.1% value = [1.0, 0.0] class = Working
Tool Wear (min) <= 1.026 entropy = 0.236 samples = 42.8% value = [0.961, 0.039] class = Working
Temp Diff (C) <= 1.353 entropy = 0.403 samples = 3.7% value = [0.08, 0.92] class = Fail
entropy = 0.915 samples = 7.6% value = [0.33, 0.67] class = Fail
entropy = 0.493 samples = 2.4% value = [0.108, 0.892] class = Fail
entropy = 0.195 samples = 2.2% value = [0.97, 0.03] class = Working
entropy = 0.233 samples = 7.1% value = [0.038, 0.962] class = Fail
entropy = 0.194 samples = 41.6% value = [0.97, 0.03] class = Working
entropy = 0.933 samples = 1.2% value = [0.651, 0.349] class = Working
entropy = 0.954 samples = 0.6% value = [0.375, 0.625] class = Fail
entropy = 0.178 samples = 3.1% value = [0.027, 0.973] class = Fail

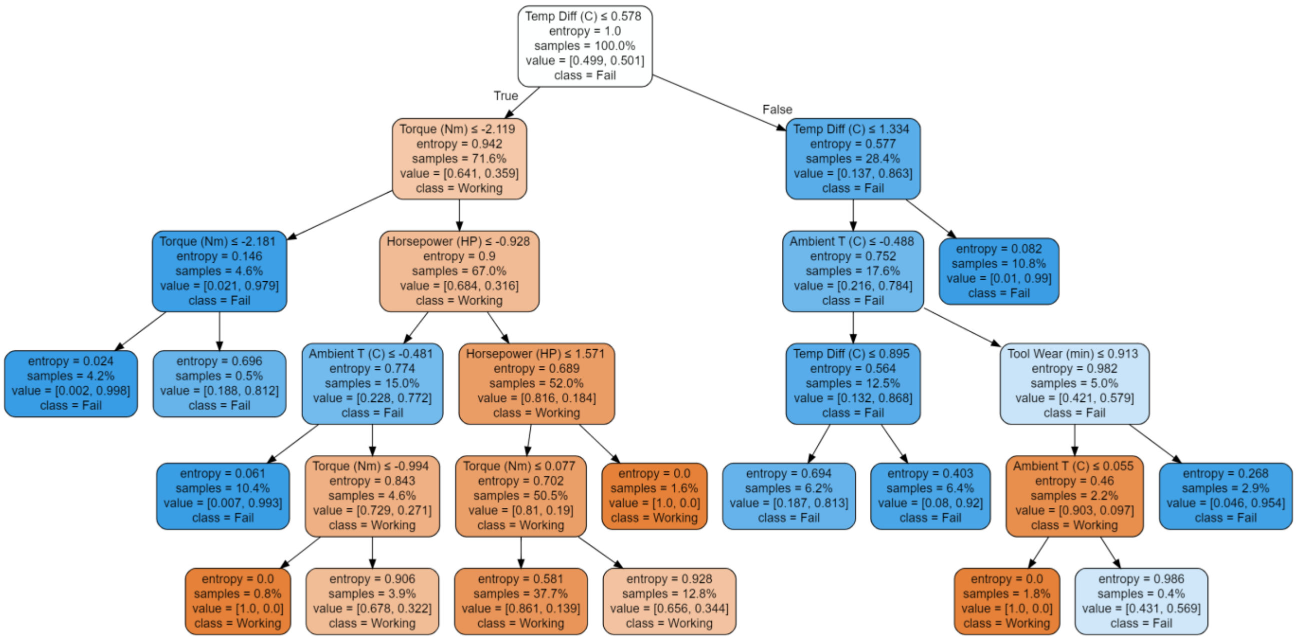
Interpreting the Model - RandomForestClassifier

```
In [ ]: sub_tree_42 = tuned_tree_clf[-1][42]
        dot_data = export_graphviz(
            sub_tree_42,
            out_file=None,
            filled=True,
            rounded=True,
            special_characters=True,
            proportion=True,
            impurity=True,  # enable them if you want
            feature_names=X_scale_train.columns,
            class_names=["Working", "Fail"],
        )
        print(dot_data)
```

```
digraph Tree {
node [shape=box, style="filled, rounded", color="black", fontname="helvetica"] ;
edge [fontname="helvetica"] ;
0 [label=<Temp Diff (C) &le; 0.578<br/>entropy = 1.0<br/>samples = 100.0%<br/>value = [0.499,
0.501]<br/>class = Fail>, fillcolor="#feffff"] ;
1 [label=<Torque (Nm) &le; -2.119<br/>entropy = 0.942<br/>samples = 71.6%<br/>value = [0.641,
0.359]<br/>class = Working>, fillcolor="#f4c8a8"] ;
0 -> 1 [labeldistance=2.5, labelangle=45, headlabel="True"] ;
3 [label=<Torque (Nm) &le; -2.181<br/>entropy = 0.146<br/>samples = 4.6%<br/>value = [0.021,
0.979]<br/>class = Fail>, fillcolor="#3d9fe6"] ;
1 -> 3 ;
23 [label=<entropy = 0.024<br/>samples = 4.2%<br/>value = [0.002, 0.998]<br/>class = Fail>, f
illcolor="#399de5"] ;
3 -> 23 ;
24 [label=<entropy = 0.696<br/>samples = 0.5%<br/>value = [0.188, 0.812]<br/>class = Fail>, f
illcolor="#67b4eb"] ;
3 -> 24 ;
4 [label=<Horsepower (HP) &le; -0.928<br/>entropy = 0.9<br/>samples = 67.0%<br/>value = [0.68
4, 0.316]<br/>class = Working>, fillcolor="#f1bb95"] ;
1 -> 4 ;
5 [label=<Ambient T (C) &le; -0.481<br/>entropy = 0.774<br/>samples = 15.0%<br/>value = [0.22
8, 0.772]<br/>class = Fail>, fillcolor="#73baed"] ;
4 -> 5 ;
7 [label=<entropy = 0.061<br/>samples = 10.4%<br/>value = [0.007, 0.993]<br/>class = Fail>, f
illcolor="#3a9ee5"] ;
5 -> 7 ;
8 [label=<Torque (Nm) &le; -0.994<br/>entropy = 0.843<br/>samples = 4.6%<br/>value = [0.729,
0.271]<br/>class = Working>, fillcolor="#efb083"] ;
5 -> 8 ;
21 [label=<entropy = 0.0<br/>samples = 0.8%<br/>value = [1.0, 0.0]<br/>class = Working>, fill
color="#e58139"] ;
8 -> 21 ;
22 [label=<entropy = 0.906<br/>samples = 3.9%<br/>value = [0.678, 0.322]<br/>class = Working
>, fillcolor="#f1bd97"] ;
8 -> 22 ;
6 [label=<Horsepower (HP) &le; 1.571<br/>entropy = 0.689<br/>samples = 52.0%<br/>value = [0.8
16, 0.184]<br/>class = Working>, fillcolor="#eb9d66"] ;
4 -> 6 ;
17 [label=<Torque (Nm) &le; 0.077<br/>entropy = 0.702<br/>samples = 50.5%<br/>value = [0.81,
0.19]<br/>class = Working>, fillcolor="#eb9f68"] ;
6 -> 17 ;
19 [label=<entropy = 0.581<br/>samples = 37.7%<br/>value = [0.861, 0.139]<br/>class = Working
>, fillcolor="#e99559"] ;
17 -> 19 ;
20 [label=<entropy = 0.928<br/>samples = 12.8%<br/>value = [0.656, 0.344]<br/>class = Working
>, fillcolor="#f3c3a1"] ;
17 -> 20 ;
18 [label=<entropy = 0.0<br/>samples = 1.6%<br/>value = [1.0, 0.0]<br/>class = Working>, fill
color="#e58139"] ;
6 -> 18 ;
2 [label=<Temp Diff (C) &le; 1.334<br/>entropy = 0.577<br/>samples = 28.4%<br/>value = [0.13
7, 0.863]<br/>class = Fail>, fillcolor="#59ade9"] ;
0 -> 2 [labeldistance=2.5, labelangle=-45, headlabel="False"] ;
9 [label=<Ambient T (C) &le; -0.488<br/>entropy = 0.752<br/>samples = 17.6%<br/>value = [0.21
6, 0.784]<br/>class = Fail>, fillcolor="#6fb8ec"] ;
2 -> 9 ;
11 [label=<Temp Diff (C) &le; 0.895<br/>entropy = 0.564<br/>samples = 12.5%<br/>value = [0.13
2, 0.868]<br/>class = Fail>, fillcolor="#57ace9"] ;
9 -> 11 ;
25 [label=<entropy = 0.694<br/>samples = 6.2%<br/>value = [0.187, 0.813]<br/>class = Fail>, f
illcolor="#66b3eb"] ;
11 -> 25 ;
26 [label=<entropy = 0.403<br/>samples = 6.4%<br/>value = [0.08, 0.92]<br/>class = Fail>, fil
lcolor="#4aa6e7"] ;
11 -> 26 ;
12 [label=<Tool Wear (min) &le; 0.913<br/>entropy = 0.982<br/>samples = 5.0%<br/>value = [0.4
21, 0.579]<br/>class = Fail>, fillcolor="#c9e4f8"] ;
9 -> 12 ;
13 [label=<Ambient T (C) &le; 0.055<br/>entropy = 0.46<br/>samples = 2.2%<br/>value = [0.903,
0.097]<br/>class = Working>, fillcolor="#e88f4e"] ;
12 -> 13 ;
15 [label=<entropy = 0.0<br/>samples = 1.8%<br/>value = [1.0, 0.0]<br/>class = Working>, fill
color="#e58139"] ;
13 -> 15 ;
16 [label=<entropy = 0.986<br/>samples = 0.4%<br/>value = [0.431, 0.569]<br/>class = Fail>, f
illcolor="#cfe7f9"] ;
13 -> 16 ;
14 [label=<entropy = 0.268<br/>samples = 2.9%<br/>value = [0.046, 0.954]<br/>class = Fail>, f
illcolor="#42a2e6"] ;
12 -> 14 ;
10 [label=<entropy = 0.082<br/>samples = 10.8%<br/>value = [0.01, 0.99]<br/>class = Fail>, fi
llcolor="#3b9ee5"] ;
2 -> 10 ;
}
```

Using the online GraphViz, a open source graph visualization software, we are able to visualise the RandomForestClassifier

Click here to view the visualization


Temp Diff (C) ≤ 0.578 entropy = 1.0 samples = 100.0% value = [0.499, 0.501] class = Fail
True
False
Torque (Nm) ≤ -2.119 entropy = 0.942 samples = 71.6% value = [0.641, 0.359] class = Working
Temp Diff (C) ≤ 1.334 entropy = 0.577 samples = 28.4% value = [0.137, 0.863] class = Fail
Torque (Nm) ≤ -2.181 entropy = 0.146 samples = 4.6% value = [0.021, 0.979] class = Fail
Horsepower (HP) ≤ -0.928 entropy = 0.9 samples = 67.0% value = [0.684, 0.316] class = Working
Ambient T (C) ≤ -0.488 entropy = 0.752 samples = 17.6% value = [0.216, 0.784] class = Fail
entropy = 0.082 samples = 10.8% value = [0.01, 0.99] class = Fail
entropy = 0.024 samples = 4.2% value = [0.002, 0.998] class = Fail
entropy = 0.696 samples = 0.5% value = [0.188, 0.812] class = Fail
Ambient T (C) ≤ -0.481 entropy = 0.774 samples = 15.0% value = [0.228, 0.772] class = Fail
Horsepower (HP) ≤ 1.571 entropy = 0.689 samples = 52.0% value = [0.816, 0.184] class = Working
Temp Diff (C) ≤ 0.895 entropy = 0.564 samples = 12.5% value = [0.132, 0.868] class = Fail
Tool Wear (min) ≤ 0.913 entropy = 0.982 samples = 5.0% value = [0.421, 0.579] class = Fail
entropy = 0.061 samples = 10.4% value = [0.007, 0.993] class = Fail
Torque (Nm) ≤ -0.994 entropy = 0.843 samples = 4.6% value = [0.729, 0.271] class = Working
Torque (Nm) ≤ 0.077 entropy = 0.702 samples = 50.5% value = [0.81, 0.19] class = Working
entropy = 0.0 samples = 1.6% value = [1.0, 0.0] class = Working
entropy = 0.694 samples = 6.2% value = [0.187, 0.813] class = Fail
entropy = 0.403 samples = 6.4% value = [0.08, 0.92] class = Fail
Ambient T (C) ≤ 0.055 entropy = 0.46 samples = 2.2% value = [0.903, 0.097] class = Working
entropy = 0.268 samples = 2.9% value = [0.046, 0.954] class = Fail
entropy = 0.0 samples = 0.8% value = [1.0, 0.0] class = Working
entropy = 0.906 samples = 3.9% value = [0.678, 0.322] class = Working
entropy = 0.581 samples = 37.7% value = [0.861, 0.139] class = Working
entropy = 0.928 samples = 12.8% value = [0.656, 0.344] class = Working
entropy = 0.0 samples = 1.8% value = [1.0, 0.0] class = Working
entropy = 0.986 samples = 0.4% value = [0.431, 0.569] class = Fail

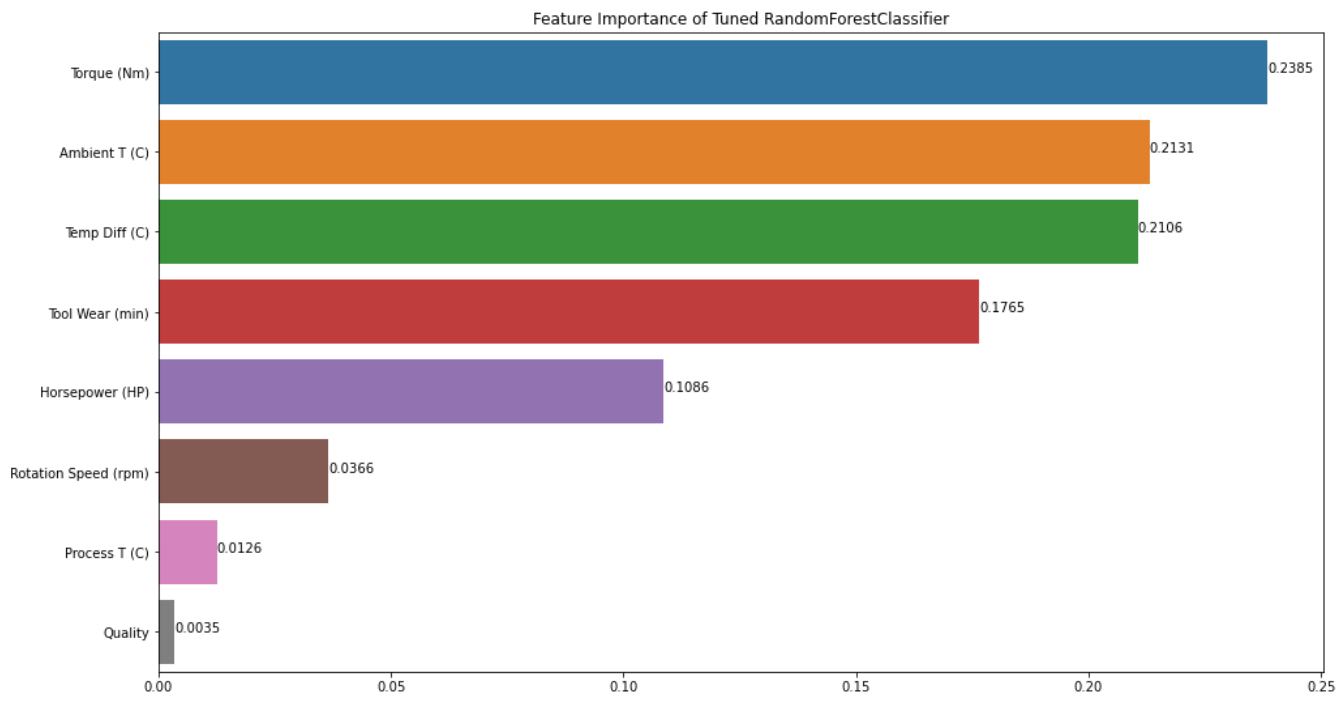
Observations

- Ambient T (C) is one of the main feature as it is able to split at the root into machine that fail and work as it is able to separate 0.704 and 0.839 samples of fail and working
- Tool Wear (min) is one of the important feature at is able to split between machine failure and machine working

Features Importance

In [ ]:
```
importance = pd.Series(
    tuned_tree_clf[-1].feature_importances_, index=X_scale_train.columns
).sort_values(ascending=False)
fig, ax = plt.subplots(figsize=(16, 9))
```

```
sns.barplot(
    x=importance[importance > 0].values, y=importance[importance > 0].index, ax=ax
)
ax.set_title("Feature Importance of Tuned {}".format("RandomForestClassifier"))
[
    ax.text(x=v, y=i, s=round(v, 4))
    for i, v in zip(np.arange(0, len(importance)), importance[importance > 0].values)
]
plt.show()
```



Observations

Torque (Nm), Tool Wear (min) and Temp Diff (C) is one of the important features for our model.

Summary

We have successfully created a model that is able to predict if the machine has failed. Through extensive feature engineering, we have been able to develop a simple model that is able to predict if the machine has failed. However, the model still faces some limitations. It has only been trained and tested on synthetically generated data, there are other factors that affects machine status like power overload from electricity. For the model to be fully deployed, it is necessary to collect more data and test it on real life examples.

Personal Learning Reflection

The difficulty I found doing the prediction task was being able to implement a pipeline for individual columns. This allowed me to learn about sci-kit learn transformers. In terms of Feature Engineering, I learn that knowing the context of the dataset is super important and allows us to do feature engineering easily.