Reduce maintenance cost through predictive techniques

Background

Company (3D Technologies) has a fleet of devices transmitting daily aggregated telemetry attributes. Predictive maintenance techniques are designed to help determine the condition of in-service equipment in order to predict when maintenance should be performed. This approach promises cost savings over routine or time-based preventive maintenance, because tasks are performed only when warranted.

Goal

You are tasked with building a predictive model using machine learning to predict the probability of a device failure. When building this model, be sure to minimize false positives and false negatives. The column you are trying to predict is called failure with binary value 0 for non-failure and 1 for failure

Data ¶

the data used can be downloaded on the following link.

link: [http://aws-proserve-data-science.s3.amazonaws.com/device_failure.csv (http://aws-proserve-data-science.s3.amazonaws.com/device_failure.csv)](http://aws-proserve-data-science.s3.amazonaws.com/device_failure.csv)

Import Packages

In [68]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from xgboost import XGBClassifier
from xgboost import XGBClassifier
from functions.main_functions import plot_curve_roc
import os
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb
from sklearn.metrics import confusion_matrix,accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
import imblearn
from imblearn.over_sampling import SMOTE
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
# import numpy as np
# import math
# import pandas as pd
# from sklearn.preprocessing import StandardScaler
# from sklearn import preprocessing
# # from sklearn.decomposition import PCA
# from sklearn.model_selection import train_test_split

# from sklearn.ensemble import RandomForestRegressor
# from sklearn.tree import DecisionTreeClassifier
# from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
```

In [ ]:

In [2]:
```
# Load data and specify encoding
df = pd.read_csv('device_failure.csv', encoding='ISO-8859-1')
```

In [3]:
```
# Inspect the data
print(df.shape)
df.head()
```

```
(124494, 12)
```

Out[3]:

	date	device	failure	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	attri
0	2015-01-01	S1F01085	0	215630672	56	0	52	6	407438	
1	2015-01-01	S1F0166B	0	61370680	0	3	0	6	403174	
2	2015-01-01	S1F01E6Y	0	173295968	0	0	0	12	237394	
3	2015-01-01	S1F01JE0	0	79694024	0	0	0	6	410186	
4	2015-01-01	S1F01R2B	0	135970480	0	0	0	15	313173	

In [ ]:

In [4]:
```
df['device'].value_counts()
```

Out[4]:
```
S1F0GGPP    304
Z1F0GE1M    304
S1F0EGMT    304
W1F05X69    304
W1F0G9T7    304
           ...
S1F0LEBM      5
Z1F14Z4F      5
S1F04KSC      4
W1F0WJFT      3
W1F1DA5ÿ      1
Name: device, Length: 1169, dtype: int64
```

In [5]:
```
print('Number of unique devices:', len(df.device.unique()))
```

```
Number of unique devices: 1169
```

Out of all the data readings we only have `1169` devices

In [6]:
```
df.nunique()
```

Out[6]:
```
date              304
device           1169
failure             2
attribute1     123877
attribute2        558
attribute3         47
attribute4        115
attribute5         60
attribute6      44838
attribute7         28
attribute8         28
attribute9         65
dtype: int64
```

In [7]:
```
df.head()
```

Out[7]:

	date	device	failure	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	attri
0	2015-01-01	S1F01085	0	215630672	56	0	52	6	407438	
1	2015-01-01	S1F0166B	0	61370680	0	3	0	6	403174	
2	2015-01-01	S1F01E6Y	0	173295968	0	0	0	12	237394	
3	2015-01-01	S1F01JE0	0	79694024	0	0	0	6	410186	
4	2015-01-01	S1F01R2B	0	135970480	0	0	0	15	313173	

In [8]:
```
df['failure'].value_counts()
```

Out[8]:
```
0    124388
1       106
Name: failure, dtype: int64
```

The predictor variable `"failure"` has two binary values

- `Failure` with binary value 1
- `Non-failure` with binary value 0

The Total number of failure:106 The Total number of Non-failure:124388

In [9]:
```
df['date'].head()
```

Out[9]:
```
0    2015-01-01
1    2015-01-01
2    2015-01-01
3    2015-01-01
4    2015-01-01
Name: date, dtype: object
```

In [10]:
```
df['date'].tail()
```

Out[10]:
```
124489    2015-11-02
124490    2015-11-02
124491    2015-11-02
124492    2015-11-02
124493    2015-11-02
Name: date, dtype: object
```

In [11]:
```
print('Start date:\t\t',min(df['date']))
print('End / latest date:\t',max(df['date']))
```

```
Start date:              2015-01-01
End / latest date:       2015-11-02
```

The device sensors started recording data on `2015-01-01` , and the latest date was on `2015-11-02`

EDA

In [12]:
```
df.head()
```

Out[12]:

	date	device	failure	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	attri
0	2015-01-01	S1F01085	0	215630672	56	0	52	6	407438	
1	2015-01-01	S1F0166B	0	61370680	0	3	0	6	403174	
2	2015-01-01	S1F01E6Y	0	173295968	0	0	0	12	237394	
3	2015-01-01	S1F01JE0	0	79694024	0	0	0	6	410186	
4	2015-01-01	S1F01R2B	0	135970480	0	0	0	15	313173	

In [15]:
```
df.describe().T
```

Out[15]:

	count	mean	std	min	25%	50%	75%	
failure	124494.0	8.514467e-04	2.916725e-02	0.0	0.0	0.0	0.0	
attribute1	124494.0	1.223881e+08	7.045933e+07	0.0	61284762.0	122797388.0	183309640.0	2441
attribute2	124494.0	1.594848e+02	2.179658e+03	0.0	0.0	0.0	0.0	
attribute3	124494.0	9.940455e+00	1.857473e+02	0.0	0.0	0.0	0.0	
attribute4	124494.0	1.741120e+00	2.290851e+01	0.0	0.0	0.0	0.0	
attribute5	124494.0	1.422267e+01	1.594303e+01	1.0	8.0	10.0	12.0	
attribute6	124494.0	2.601727e+05	9.915108e+04	8.0	221452.0	249799.5	310266.0	6
attribute7	124494.0	2.925282e-01	7.436924e+00	0.0	0.0	0.0	0.0	
attribute8	124494.0	2.925282e-01	7.436924e+00	0.0	0.0	0.0	0.0	
attribute9	124494.0	1.245152e+01	1.914256e+02	0.0	0.0	0.0	0.0	

In [18]:
```
df.columns.to_list()
```

Out[18]:
```
['date',
 'device',
 'failure',
 'attribute1',
 'attribute2',
 'attribute3',
 'attribute4',
 'attribute5',
 'attribute6',
 'attribute7',
 'attribute8',
 'attribute9']
```

In [17]:
```
df1 = pd.melt(df, id_vars=['date', 'device','failure'],
              value_vars=['attribute1','attribute2','attribute3',
                          'attribute4','attribute5','attribute6',
                          'attribute7','attribute8','attribute9'])
```

In [18]:
```
df1
```

Out[18]:

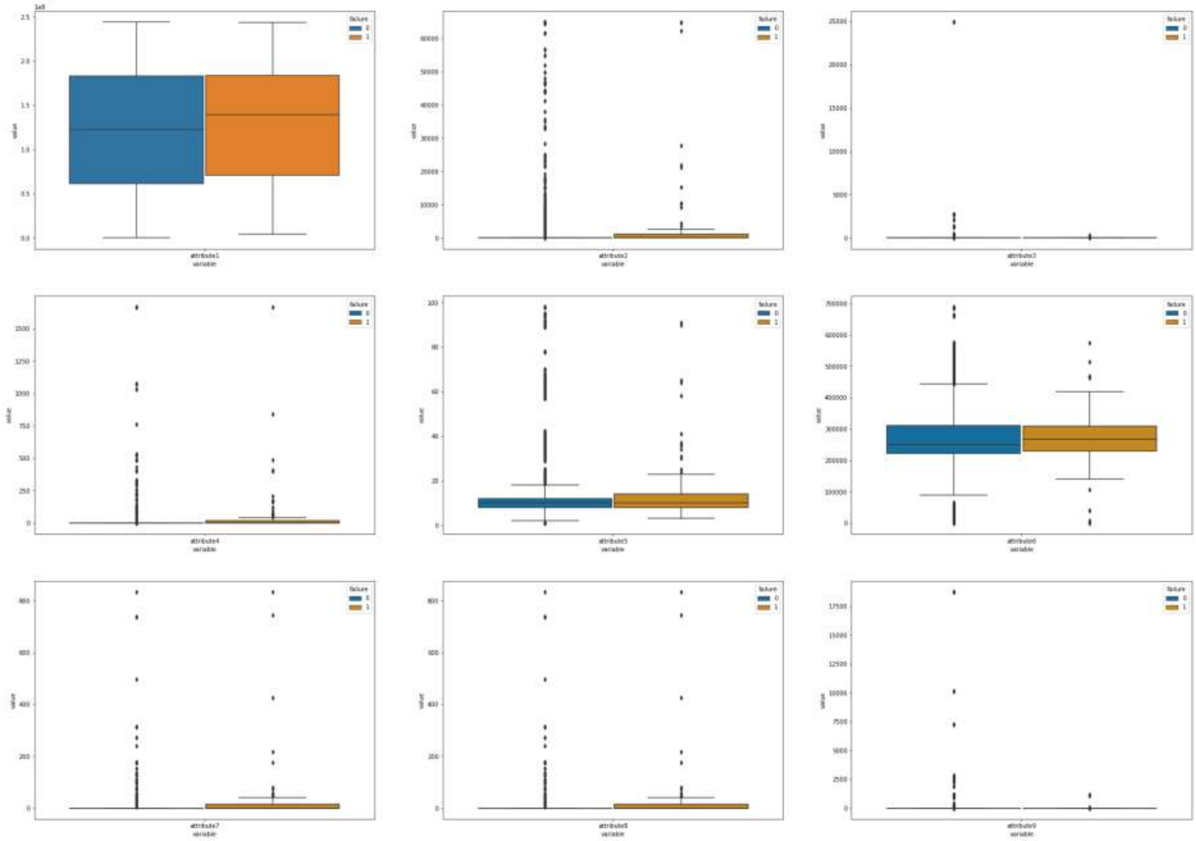
	date	device	failure	variable	value
0	2015-01-01	S1F01085	0	attribute1	215630672
1	2015-01-01	S1F0166B	0	attribute1	61370680
2	2015-01-01	S1F01E6Y	0	attribute1	173295968
3	2015-01-01	S1F01JE0	0	attribute1	79694024
4	2015-01-01	S1F01R2B	0	attribute1	135970480
...	...	...	...	...	...
1120441	2015-11-02	Z1F0MA1S	0	attribute9	0
1120442	2015-11-02	Z1F0Q8RT	0	attribute9	13
1120443	2015-11-02	Z1F0QK05	0	attribute9	0
1120444	2015-11-02	Z1F0QL3N	0	attribute9	0
1120445	2015-11-02	Z1F0QLC1	0	attribute9	0

1120446 rows × 5 columns

Investigate Outliers

In [19]:
```
fig = plt.figure(figsize=(35, 25))
ax1 =fig.add_subplot(3,3,1)
sns.boxplot(x = 'variable', y = 'value',
                 data=df1[df1['variable'].isin(['attribute1'])], hue = 'failure')

ax2 =fig.add_subplot(3,3,2)
sns.boxplot(x = 'variable', y = 'value',
                 data=df1[df1['variable'].isin(['attribute2'])], hue = 'failure',
                 palette="colorblind")

ax3 =fig.add_subplot(3,3,3)
sns.boxplot(x = 'variable', y = 'value',
                 data=df1[df1['variable'].isin(['attribute3'])], hue = 'failure',
                 palette="colorblind")

ax4 =fig.add_subplot(3,3,4)
sns.boxplot(x = 'variable', y = 'value',
                 data=df1[df1['variable'].isin(['attribute4'])], hue = 'failure',
                 palette="colorblind")

ax5 =fig.add_subplot(3,3,5)
sns.boxplot(x = 'variable', y = 'value',
                 data=df1[df1['variable'].isin(['attribute5'])], hue = 'failure',
                 palette="colorblind")

ax6 =fig.add_subplot(3,3,6)
sns.boxplot(x = 'variable', y = 'value',
                 data=df1[df1['variable'].isin(['attribute6'])], hue = 'failure',
                 palette="colorblind")

ax7 =fig.add_subplot(3,3,7)
sns.boxplot(x = 'variable', y = 'value',
                 data=df1[df1['variable'].isin(['attribute7'])], hue = 'failure',
                 palette="colorblind")

ax8 =fig.add_subplot(3,3,8)
sns.boxplot(x = 'variable', y = 'value',
                 data=df1[df1['variable'].isin(['attribute8'])], hue = 'failure',
                 palette="colorblind")

ax9 =fig.add_subplot(3,3,9)
sns.boxplot(x = 'variable', y = 'value',
                 data=df1[df1['variable'].isin(['attribute9'])], hue = 'failure',
                 palette="colorblind")
```

Out[19]:
```
<AxesSubplot:xlabel='variable', ylabel='value'>
```

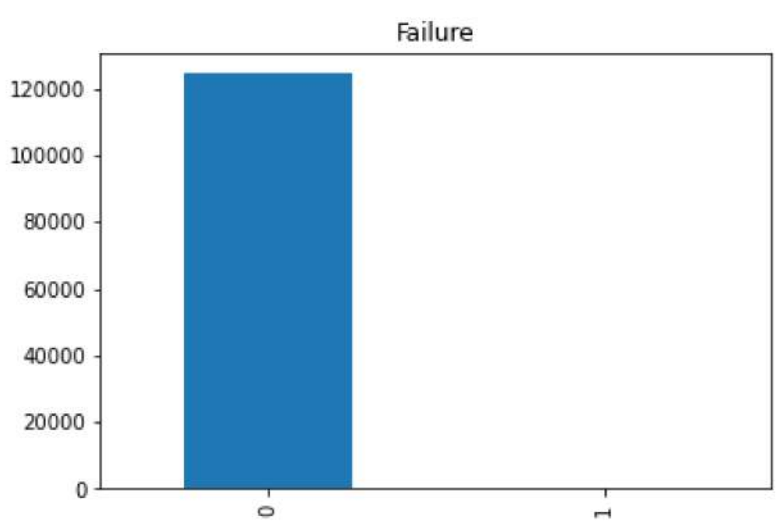


From the Plots above it's clear that attribute1 has no outliers in both failure and non-failure classes, whereas the following attributes from attribute2 to attribute9 has extreme outliers as it is also shown from the summary statistic that the mean is a bit higher than the median and the distance between the 75th percentile and Max is extreme

In [ ]:

In [24]:
```
df['failure'].value_counts().plot(kind='bar', title = 'Failure')
```

Out[24]: <AxesSubplot:title={'center':'Failure'}>



In [ ]:

Probabbility of a class being correctly predicted

In [20]:
```
print('failure    :\t',round(len(df[df['failure'] ==1])/len(df)*100, 3),'%')
print('non-failure:\t',round(len(df[df['failure'] == 0])/len(df)*100, 3),'%')
```

```
failure    :	0.085 %
non-failure:	99.915 %
```

A model would mostly predict `non-failure` . our model would predict the class correctly approximatley 99.9% of the time this is due because of the class imbalance. To assess the models we fit, I will compare them to this baseline. I will later use SNOTE to balance the data

Pre-Processing

We will start by pre-processing the data so that we can run it through the model.

This involves:

- Splitting the data into features and labels;
- Standardise the data using `sklearn` 's `StandardScaler` ;
- Splitting the data into training and testing data.

Feature Scaling

In [26]:
```
# from sklearn.preprocessing import StandardScaler

# sc = StandardScaler()
# X_train = sc.fit_transform(X_train)
# X_test = sc.transform(X_test)
```

Model Training and Assessing

In [21]:
```
df.head()
```

Out[21]:

	date	device	failure	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	attri
0	2015-01-01	S1F01085	0	215630672	56	0	52	6	407438	
1	2015-01-01	S1F0166B	0	61370680	0	3	0	6	403174	
2	2015-01-01	S1F01E6Y	0	173295968	0	0	0	12	237394	
3	2015-01-01	S1F01JE0	0	79694024	0	0	0	6	410186	
4	2015-01-01	S1F01R2B	0	135970480	0	0	0	15	313173	

In [22]:
```
# Predictor Variavbles
X = df.drop(['failure','device','date'], axis = 1).values

# Response Variables
y = df['failure']
```

In [23]:
```
print('Predictor Variavbles \n',X,'\n\nResponse Variables\n',
      y[0:5])
```

```
Predictor Variavbles
 [[215630672        56         0 ...         0         0         7]
 [ 61370680         0         3 ...         0         0         0]
 [173295968         0         0 ...         0         0         0]
 ...
 [ 19029120      4832         0 ...         0         0         0]
 [226953408         0         0 ...         0         0         0]
 [ 17572840         0         0 ...         0         0         0]]

Response Variables
 0    0
1    0
2    0
3    0
4    0
Name: failure, dtype: int64
```

In [24]:
```
# Status Details - Target variable
#-1 = failure,
#-0 = non-failure,

df.failure.value_counts()
```

Out[24]:
```
0    124388
1       106
Name: failure, dtype: int64
```

Splitting the dataset into the Training set and Test set

In [25]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30, rando
```

In [ ]:
```
```

Decision Tree Classifier

Decision trees, which are the foundation of all tree-based models.

Training

In [30]:
```
dt_classifier = DecisionTreeClassifier(random_state=42)
dt_classifier.fit(X_train, y_train)
```

Out[30]:
```
DecisionTreeClassifier(random_state=42)
```

Testing

In [31]:
```
y_pred = dt_classifier.predict(X_test)
```

In [32]:
```
## counting values in each class we have in this testset
y_test.value_counts()
```

Out[32]:
```
0    37319
1       30
Name: failure, dtype: int64
```

In [33]:
```
classes = ['non-failure', 'failure']

pd.DataFrame(data=confusion_matrix(y_test, y_pred), index=classes, columns=classe
```

Out[33]:

	non-failure	failure
non-failure	37295	24
failure	27	3

The model can classify most of the classes correcly... I'll also take a look at the classification report for the predicted values the check the accuracy score.

In [36]:
```
print(classification_report(y_test, y_pred, target_names = ['non-failure', 'failu
```

```
              precision    recall  f1-score   support

 non-failure       1.00      1.00      1.00     37319
     failure       0.11      0.10      0.11        30

    accuracy                           1.00     37349
   macro avg       0.56      0.55      0.55     37349
weighted avg       1.00      1.00      1.00     37349
```

In [37]:
```
accuracy_score(y_test, y_pred)
```

Out[37]: 0.9986345015930814

Overfitting turns out to be a general property of decision tree, however it can be avoided by using

- **Pre-pruning** that stop growing the tree earlier, before it perfectly classifies the training set.
- **Post-pruning** that allows the tree to perfectly classify the training set, and then post prune the tree.

We will explore the above later

[avoiding overfitting - Decision Tree (https://www.saedsayad.com/decision_tree_overfitting.htm#:~:text=increased%20test%20set%20err](https://www.saedsayad.com/decision_tree_overfitting.htm#:~:text=increased%20test%20set%20err)

Random Forest

Random forest, is an "**ensemble**" method which builds many decision trees in parallel.

They can be trained quickly. Since trees do not rely on one another, they can be trained in parallel.

Training

In [38]:
```
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
rf_classifier.fit(X_train, y_train)
```

Out[38]:
```
RandomForestClassifier(random_state=42)
```

Testing

In [39]:
```
## counting values in each class we have in this testset
y_test.value_counts()
```

Out[39]:
```
0    37319
1       30
Name: failure, dtype: int64
```

In [40]:
```
# predict classes
y_pred = rf_classifier.predict(X_test)
```

In [41]:
```
classes = ['non-failure', 'failure']

pd.DataFrame(data=confusion_matrix(y_test, y_pred), index=classes, columns=classe
```

Out[41]:

	non-failure	failure
non-failure	37314	5
failure	30	0

In [42]:
```
print(classification_report(y_test, y_pred, target_names = ['non-failure', 'failu
```

```
              precision    recall  f1-score   support

 non-failure       1.00      1.00      1.00     37319
     failure       0.00      0.00      0.00        30

    accuracy                           1.00     37349
   macro avg       0.50      0.50      0.50     37349
weighted avg       1.00      1.00      1.00     37349
```

Gradient Boost

Gradient boosting, is an “**ensemble**” method which builds many decision trees sequentially. They are good at dealing with imbalanced data, but slower to train, since trees must be built sequentially

Training

In [46]:
```
gb_classifier = GradientBoostingClassifier(random_state=42)
gb_classifier.fit(X_train, y_train)
```

Out[46]:
```
GradientBoostingClassifier(random_state=42)
```

Testing

In [47]:
```
## counting values in each class we have in this testset
y_test.value_counts()
```

Out[47]:
```
0    37319
1       30
Name: failure, dtype: int64
```

In [48]:
```
# predict classes
y_pred = gb_classifier.predict(X_test)
```

In [49]:
```
classes = ['non-failure', 'failure']

pd.DataFrame(data=confusion_matrix(y_test, y_pred), index=classes, columns=classe
```

Out[49]:

	non-failure	failure
non-failure	37308	11
failure	27	3

In [50]:
```
print(classification_report(y_test, y_pred, target_names = ['non-failure', 'failu
```

```
              precision    recall  f1-score   support

 non-failure       1.00      1.00      1.00     37319
     failure       0.21      0.10      0.14        30

    accuracy                           1.00     37349
   macro avg       0.61      0.55      0.57     37349
weighted avg       1.00      1.00      1.00     37349
```

KNeighbors Classifier

Training

In [51]:
```
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train, y_train)
```

Out[51]:
```
KNeighborsClassifier(n_neighbors=3)
```

Testing

In [52]:
```
# predict classes
y_pred = knn.predict(X_test)
```

In [53]:
```
classes = ['non-failure', 'failure']

pd.DataFrame(data=confusion_matrix(y_test, y_pred), index=classes, columns=classe
```

Out[53]:

	non-failure	failure
non-failure	37319	0
failure	30	0

In [55]:
```
print(classification_report(y_test, y_pred, target_names = ['non-failure', 'failu
```

```
              precision    recall  f1-score   support

 non-failure       1.00      1.00      1.00     37319
     failure       0.00      0.00      0.00        30

    accuracy                           1.00     37349
   macro avg       0.50      0.50      0.50     37349
weighted avg       1.00      1.00      1.00     37349
```

XGBoost model

Training

In [56]:
```
xgb = XGBClassifier(random_state=0)
xgb.fit(X_train, y_train)
```

```
[21:44:56] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.
0/src/learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric
used with the objective 'binary:logistic' was changed from 'error' to 'loglos
s'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

Out[56]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=4, num_parallel_tree=1, random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

Testing

In [57]:
```
# predict classes
y_pred = xgb.predict(X_test)
```

In [58]:
```
classes = ['non-failure', 'failure']

pd.DataFrame(data=confusion_matrix(y_test, y_pred), index=classes, columns=classe
```

Out[58]:

	non-failure	failure
non-failure	37314	5
failure	30	0

In [59]:
```
print(classification_report(y_test, y_pred, target_names = ['non-failure', 'failu
```

```
              precision    recall  f1-score   support

 non-failure       1.00      1.00      1.00     37319
     failure       0.00      0.00      0.00        30

    accuracy                           1.00     37349
   macro avg       0.50      0.50      0.50     37349
weighted avg       1.00      1.00      1.00     37349
```

From all the above trained models we can see that they cannot predict failure because they are suffering from DATA IMBALANCE and that results in the model being biased to the majority class

Data Balance

In [60]:
```
from imblearn.over_sampling import SMOTE
oversample = SMOTE(random_state=42)
X_trainos, y_trainos = oversample.fit_resample(X_train, y_train)
```

Decision Tree Classifier

Training

In [61]:
```

dt_classifier = DecisionTreeClassifier(random_state=42)
dt_classifier.fit(X_trainos, y_trainos)
```

Out[61]:
```
DecisionTreeClassifier(random_state=42)
```

Testing

In [62]:
```
y_pred = dt_classifier.predict(X_test)
```

In [63]:
```
## counting values in each class we have in this testset
y_test.value_counts()
```

Out[63]:
```
0    37319
1       30
Name: failure, dtype: int64
```

In [64]:
```
classes = ['non-failure', 'failure']
pd.DataFrame(data=confusion_matrix(y_test, y_pred), index=classes, columns=classe
```

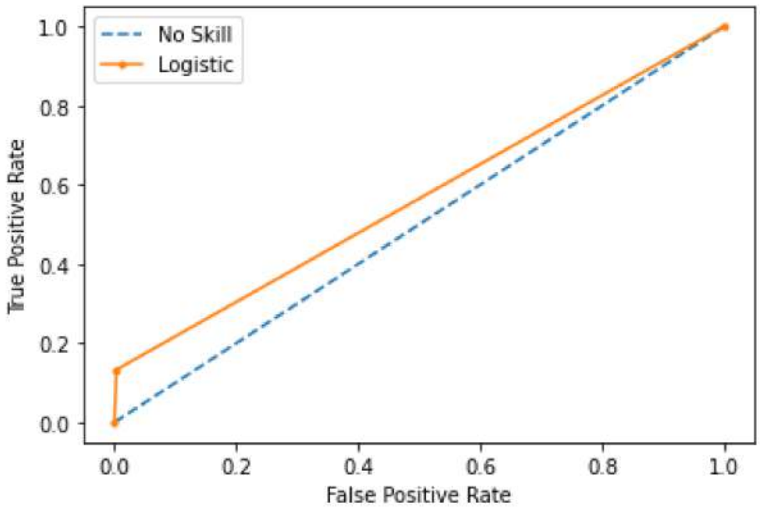
Out[64]:

	non-failure	failure
non-failure	37191	128
failure	26	4

In [65]:
```
print(classification_report(y_test, y_pred, target_names = ['non-failure', 'failu
```

```
              precision    recall  f1-score   support

 non-failure       1.00      1.00      1.00     37319
     failure       0.03      0.13      0.05        30

    accuracy                           1.00     37349
   macro avg       0.51      0.56      0.52     37349
weighted avg       1.00      1.00      1.00     37349
```

In [69]:
```
plot_curve_roc(dt_classifier,X_test,y_test)
print("AUC: %.3f" % (roc_auc_score(y_test, y_pred)))
```




```
AUC: 0.565
```

Random Forest

Random forest, is an “**ensemble**” method which builds many decision trees in parallel.

They can be trained quickly. Since trees do not rely on one another, they can be trained in parallel.

Training

In [70]:
```
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
rf_classifier.fit(X_trainos, y_trainos)
```

Out[70]:
```
RandomForestClassifier(random_state=42)
```

Testing

In [71]:
```
## counting values in each class we have in this testset
y_test.value_counts()
```

Out[71]:
```
0    37319
1       30
Name: failure, dtype: int64
```

In [72]:
```
# predict classes
y_pred = rf_classifier.predict(X_test)
```

In [73]:
```
classes = ['non-failure', 'failure']

pd.DataFrame(data=confusion_matrix(y_test, y_pred), index=classes, columns=classe
```

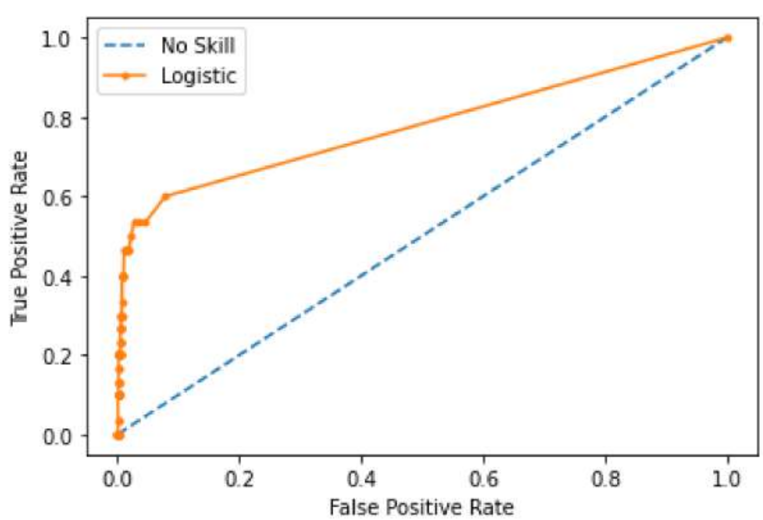
Out[73]:

	non-failure	failure
non-failure	37234	85
failure	24	6

In [74]:
```
print(classification_report(y_test, y_pred, target_names = ['non-failure', 'failu
```

```
              precision    recall  f1-score   support

 non-failure       1.00      1.00      1.00     37319
     failure       0.07      0.20      0.10        30

    accuracy                           1.00     37349
   macro avg       0.53      0.60      0.55     37349
weighted avg       1.00      1.00      1.00     37349
```

In [75]:
```
plot_curve_roc(rf_classifier,X_test,y_test)
print("AUC: %.3f" % (roc_auc_score(y_test, y_pred)))
```




```
AUC: 0.599
```

Gradient Boost

Gradient boosting, is an “**ensemble**” method which builds many decision trees sequentially. They are good at dealing with imbalanced data, but slower to train, since trees must be built sequentially

Training

In [76]:
```
gb_classifier = GradientBoostingClassifier(random_state=42)
gb_classifier.fit(X_trainos, y_trainos)
```

Out[76]:
```
GradientBoostingClassifier(random_state=42)
```

Testing

In [77]:
```
## counting values in each class we have in this testset
y_test.value_counts()
```

Out[77]:
```
0    37319
1       30
Name: failure, dtype: int64
```

In [78]:
```
# predict classes
y_pred = gb_classifier.predict(X_test)
```

In [79]:
```
classes = ['non-failure', 'failure']

pd.DataFrame(data=confusion_matrix(y_test, y_pred), index=classes, columns=classe
```

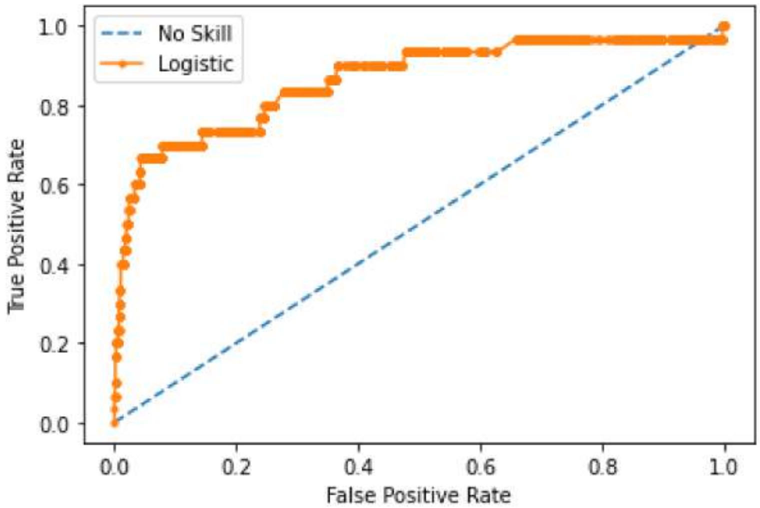
Out[79]:

	non-failure	failure
non-failure	35734	1585
failure	11	19

In [80]:
```
print(classification_report(y_test, y_pred, target_names = ['non-failure', 'failu
```

```
              precision    recall  f1-score   support

 non-failure       1.00      0.96      0.98     37319
     failure       0.01      0.63      0.02        30

    accuracy                           0.96     37349
   macro avg       0.51      0.80      0.50     37349
weighted avg       1.00      0.96      0.98     37349
```

In [81]:
```
plot_curve_roc(gb_classifier,X_test,y_test)
print("AUC: %.3f" % (roc_auc_score(y_test, y_pred)))
```




```
AUC: 0.795
```

KNeighbors Classifier

Training

In [82]:
```
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_trainos, y_trainos)
```

Out[82]:
```
KNeighborsClassifier(n_neighbors=3)
```

Testing

In [83]:
```
# predict classes
y_pred = knn.predict(X_test)
```

In [84]:
```
classes = ['non-failure', 'failure']

pd.DataFrame(data=confusion_matrix(y_test, y_pred), index=classes, columns=classe
```

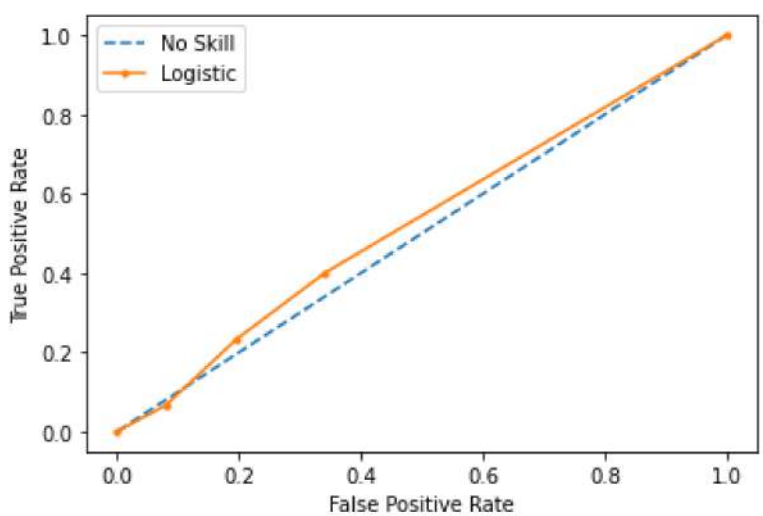
Out[84]:

	non-failure	failure
non-failure	30004	7315
failure	23	7

In [85]:
```
print(classification_report(y_test, y_pred, target_names = ['non-failure', 'failu
```

```
              precision    recall  f1-score   support

 non-failure       1.00      0.80      0.89     37319
     failure       0.00      0.23      0.00        30

    accuracy                           0.80     37349
   macro avg       0.50      0.52      0.45     37349
weighted avg       1.00      0.80      0.89     37349
```

In [86]:
```
plot_curve_roc(knn,X_test,y_test)
print("AUC: %.3f" % (roc_auc_score(y_test, y_pred)))
```




```
AUC: 0.519
```

XGBoost model

Training

In [87]:
```
xgb = XGBClassifier(random_state=0)
xgb.fit(X_trainos, y_trainos)
```

```
[21:48:45] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.
0/src/learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric
used with the objective 'binary:logistic' was changed from 'error' to 'loglos
s'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

Out[87]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=4, num_parallel_tree=1, random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

Testing

In [88]:
```
# predict classes
y_pred = xgb.predict(X_test)
```

In [89]:
```
classes = ['non-failure', 'failure']

pd.DataFrame(data=confusion_matrix(y_test, y_pred), index=classes, columns=classe
```

Out[89]:

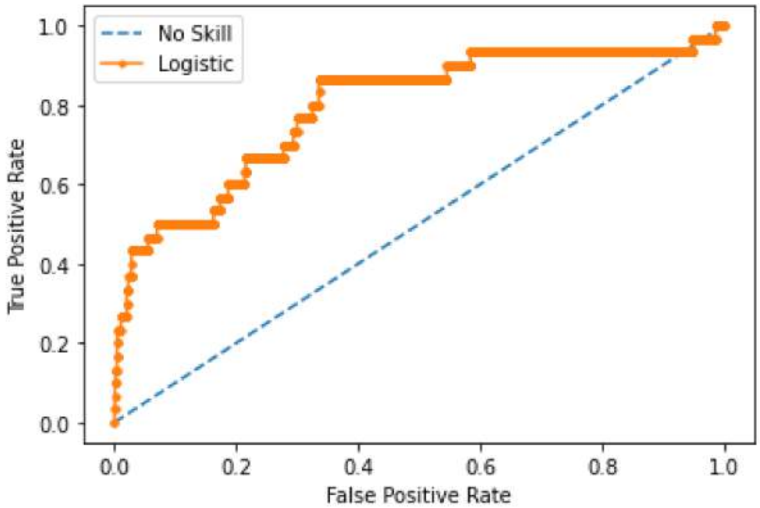
	non-failure	failure
non-failure	37140	179
failure	24	6

In [90]:
```
print(classification_report(y_test, y_pred, target_names = ['non-failure', 'failu
```

```
              precision    recall  f1-score   support

 non-failure       1.00      1.00      1.00     37319
     failure       0.03      0.20      0.06        30

    accuracy                           0.99     37349
   macro avg       0.52      0.60      0.53     37349
weighted avg       1.00      0.99      1.00     37349
```

In [91]:
```
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
```

In [92]:
```
plot_curve_roc(xgb,X_test,y_test)

print("AUC: %.3f" % (roc_auc_score(y_test, y_pred)))
```




```
AUC: 0.598
```

Feedback

I've inspected the data it has a huge imbalanced in response variable, to address that a SMOTE technique was adopted to do upsample and balance the data.

I've also trained difference classification models and Gradient Boost had accuracy score of 96% after balancing of the data and I was able to compute a AUC score of 0.795 of which was the highest in all the models which was able to correctly classify 19/30 true positives for failure and 35734/37319 true positives non-failure. the model can further be improved using GridSearch to tune it which will further minimize false positives and false negatives.

In [ ]: