Maintenance Cost Reduction Prediction Project

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A company has a fleet of devices transmitting daily telemetry readings. They would like to create a predictive maintenance solution to proactively identify when maintenance should be performed. This approach promises cost savings over routine or time-based preventive maintenance, because tasks are performed only when warranted.

The goal of this project is to predict when/which devices potentially are going to fail next. Seven predictive models have been developed as comparison and the best model is recommended after comprehensive comparison. Data has been detailedly exploratoried and additional features are created as essential indication to improve the performance.

As ever, the contents of this project are listed as below:

1. Sourcing and loading
- Import packages
- Load data
- Explore the data

2. Cleaning, transforming and visualizing
2.1 Feature engineering - category features
2.2 Further EDA - STD and PCT_Change new features
2.3 Train/test split
2.4 Imbalanced process - upsampling

3. Modeling
3.1 Model 1: Logistic Regression Model
3.2 Model 2: SVM Model
3.3 Model 3: Random Forest Model
3.4 Model 4: Decision Tree Model
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3.6 Model 6 & 7: Voting Classifer

4. Evaluating and concluding
4.1 Precision and Recall Comparison
4.2 Conclusion and Recommendation

1 Sourcing and loading

[1]:
```python
import re
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.preprocessing import scale, StandardScaler
from pathlib import Path
import numpy as np
import re
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
import math
import imblearn
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import VotingClassifier
```

[2]:
```python
df = pd.read_csv('predictive_maintenance.csv', parse_dates=['date'])
```

[3]:
```python
df.head()
```

[3]:
```
        date    device  failure    metric1  metric2  metric3  metric4  \
0 2015-01-01  S1F01085        0  215630672       56        0       52
1 2015-01-01  S1F0166B        0   61370680        0        3        0
2 2015-01-01  S1F01E6Y        0  173295968        0        0        0
3 2015-01-01  S1F01JE0        0   79694024        0        0        0
4 2015-01-01  S1F01R2B        0  135970480        0        0        0

   metric5  metric6  metric7  metric8  metric9
0        6   407438        0        0        7
1        6   403174        0        0        0
2       12   237394        0        0        0
3        6   410186        0        0        0
4       15   313173        0        0        3
```

[4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 124494 entries, 0 to 124493
Data columns (total 12 columns):
 #   Column    Non-Null Count   Dtype
---  ------    --------------   -----
 0   date      124494 non-null  datetime64[ns]
```

```
 1   device   124494 non-null  object
 2   failure  124494 non-null  int64
 3   metric1  124494 non-null  int64
 4   metric2  124494 non-null  int64
 5   metric3  124494 non-null  int64
 6   metric4  124494 non-null  int64
 7   metric5  124494 non-null  int64
 8   metric6  124494 non-null  int64
 9   metric7  124494 non-null  int64
 10  metric8  124494 non-null  int64
 11  metric9  124494 non-null  int64
dtypes: datetime64[ns](1), int64(10), object(1)
memory usage: 11.4+ MB
```

[5]:
```
df.describe()
```

[5]:
```
              failure       metric1        metric2        metric3  \
count  124494.000000  1.244940e+05  124494.000000  124494.000000
mean        0.000851  1.223881e+08     159.484762       9.940455
std         0.029167  7.045933e+07    2179.657730     185.747321
min         0.000000  0.000000e+00       0.000000       0.000000
25%         0.000000  6.128476e+07       0.000000       0.000000
50%         0.000000  1.227974e+08       0.000000       0.000000
75%         0.000000  1.833096e+08       0.000000       0.000000
max         1.000000  2.441405e+08   64968.000000   24929.000000

              metric4        metric5        metric6        metric7  \
count  124494.000000  124494.000000  124494.000000  124494.000000
mean        1.741120      14.222669  260172.657726       0.292528
std        22.908507      15.943028   99151.078547       7.436924
min         0.000000       1.000000       8.000000       0.000000
25%         0.000000       8.000000  221452.000000       0.000000
50%         0.000000      10.000000  249799.500000       0.000000
75%         0.000000      12.000000  310266.000000       0.000000
max      1666.000000      98.000000  689161.000000     832.000000

              metric8        metric9
count  124494.000000  124494.000000
mean        0.292528      12.451524
std         7.436924     191.425623
min         0.000000       0.000000
25%         0.000000       0.000000
50%         0.000000       0.000000
75%         0.000000       0.000000
max       832.000000   18701.000000
```

[6]:
```
df["failure"].value_counts()
```

[6]:
```
0    124388
1       106
Name: failure, dtype: int64
```

2 Cleaning, transforming and visualizing

2.1 Feature engineering - category features

[7]:
```
df["date"].value_counts()
```

[7]:
```
2015-01-03    1163
2015-01-01    1163
2015-01-02    1163
2015-01-04    1162
2015-01-05    1161
              ...
2015-11-02      31
2015-10-31      31
2015-10-27      31
2015-10-30      31
2015-10-29      31
Name: date, Length: 304, dtype: int64
```

[8]:
```
df["date_cat"] = df["date"].astype("category")
df["date_month"] = df['date_cat'].dt.month
df["date_weekday"] = df['date_cat'].dt.dayofweek
print(df.groupby("date_month").size())
print(df.groupby("date_weekday").size())
```

```
date_month
1     25032
2     19500
3     19833
4     12012
5     11330
6     10469
7     10531
8      8346
9      4470
10     2940
11       31
dtype: int64
date_weekday
0    17886
1    17534
2    17136
3    18141
```

```
4    18041
5    17897
6    17859
dtype: int64
```

[39]:
```
df_month = df.loc[df["failure"] == 1, ["date_month", "failure"]].
 ↪groupby(["date_month"]).agg(["sum"])
print(df_month.head())
sns.set()
df_month.plot(legend = False)
```

```
           failure
               sum
date_month
1               24
2               14
3                9
4                9
5               21
```

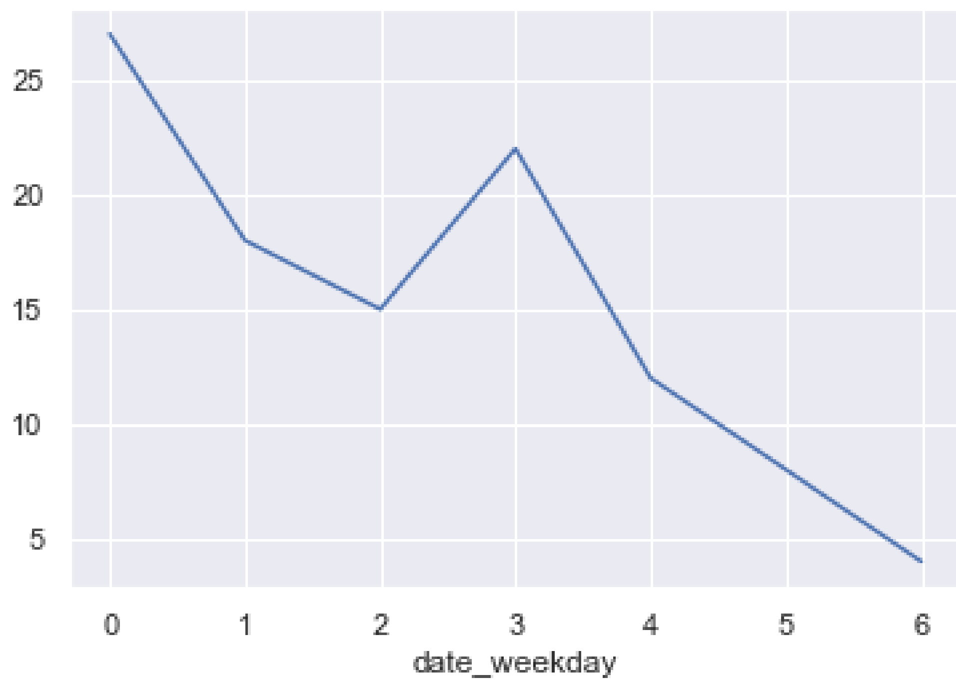
[39]: <matplotlib.axes._subplots.AxesSubplot at 0x249f27267f0>

[38]:
```
df_weekday = df.loc[df["failure"] == 1, ["date_weekday", "failure"]].
 ↪groupby(["date_weekday"]).agg(["sum"])
print(df_weekday.head())
```

```
sns.set()
df_weekday.plot(legend = False)
```

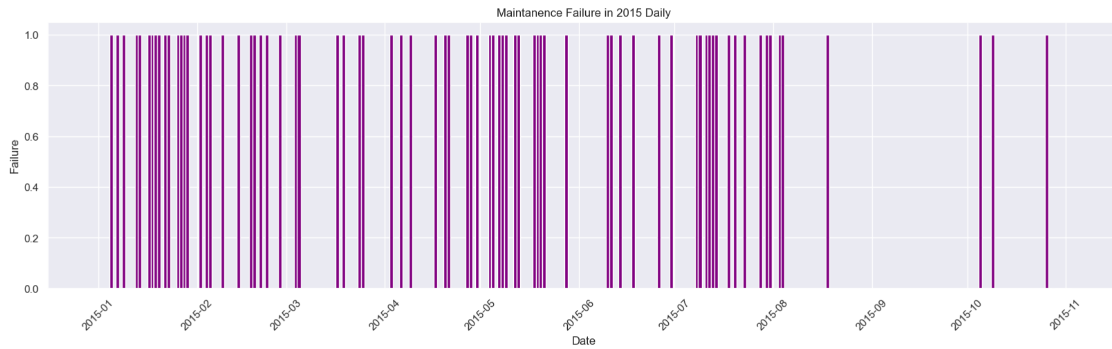
```
              failure
                  sum
date_weekday
0                  27
1                  18
2                  15
3                  22
4                  12
```

[38]: <matplotlib.axes._subplots.AxesSubplot at 0x249f28da550>



[113]:
```
# Create figure and plot space
sns.set()
fig, ax = plt.subplots(figsize=(20, 5))

# Add x-axis and y-axis
ax.bar(df["date"], df["failure"], color='purple', width=1.1)

# Set title and labels for axes
ax.set(xlabel="Date",
       ylabel="Failure",
       title="Maintanence Failure in 2015 Daily")
```

```python
# Rotate tick marks on x-axis
plt.setp(ax.get_xticklabels(), rotation=45)

plt.show()
```



[12]:
```python
df1 = df.resample('W', on='date').sum()
df1.head()
```

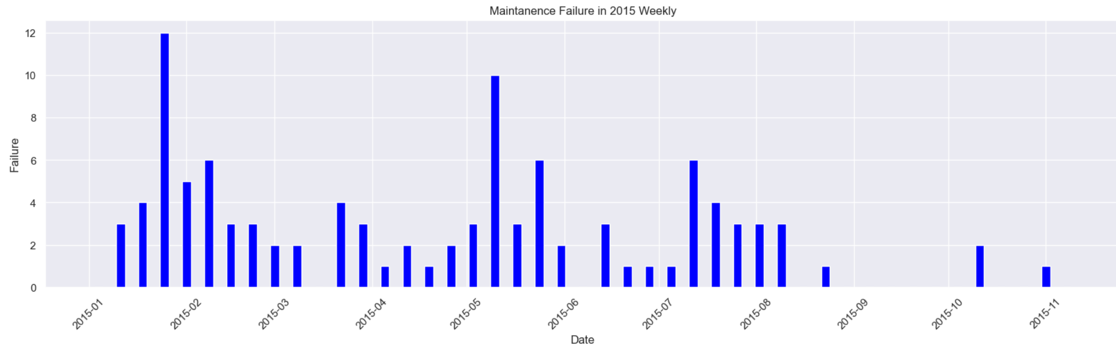
[12]:

date	failure	metric1	metric2	metric3	metric4	metric5
2015-01-04	0	574605009416	1881304	136076	19595	55809
2015-01-11	3	738576615862	2417064	47401	15881	79997
2015-01-18	4	625470313893	1281496	41508	6896	71480
2015-01-25	12	605094600044	680664	41096	6261	70815
2015-02-01	5	612405754450	705456	41078	6296	70656

date	metric6	metric7	metric8	metric9	date_month	date_weekday
2015-01-04	1108643013	3168	3168	229463	4651	20928
2015-01-11	1459948029	2142	2142	116358	6035	16247
2015-01-18	1259083398	1272	1272	70720	5085	15051
2015-01-25	1252871765	1728	1728	76906	4986	14953
2015-02-01	1257979649	1808	1808	72695	5699	14961

[112]:
```python
# Create figure and plot space
sns.set()
fig, ax = plt.subplots(figsize=(20, 5))

# Add x-axis and y-axis
ax.bar(df1.index.values, df1["failure"], color='blue', width=2.8)

# Set title and labels for axes
ax.set(xlabel="Date",
```

```python
       ylabel="Failure",
       title="Maintanence Failure in 2015 Weekly")

# Rotate tick marks on x-axis
plt.setp(ax.get_xticklabels(), rotation=45)

plt.show()
```



[18]:
```python
df2 = df.resample('M', on='date').sum()
df2.head()
```

[18]:

date	failure	metric1	metric2	metric3	metric4	metric5
2015-01-31	24	3070334591889	6850320	301287	53893	338695
2015-02-28	14	2392243498814	2874600	164742	24680	274635
2015-03-31	9	2424902863541	3302888	162419	32691	284798
2015-04-30	9	1483418760960	914432	70781	18285	184301
2015-05-31	21	1387078212434	835224	127631	32318	175243

date	metric6	metric7	metric8	metric9	date_month	date_weekday
2015-01-31	6158782773	10006	10006	556053	25032	77868
2015-02-28	4909604046	1656	1656	281360	39000	58421
2015-03-31	5061130092	2032	2032	260404	59499	58154
2015-04-30	3137391230	4560	4560	36332	48048	35722
2015-05-31	2943043116	640	640	110037	56650	36178

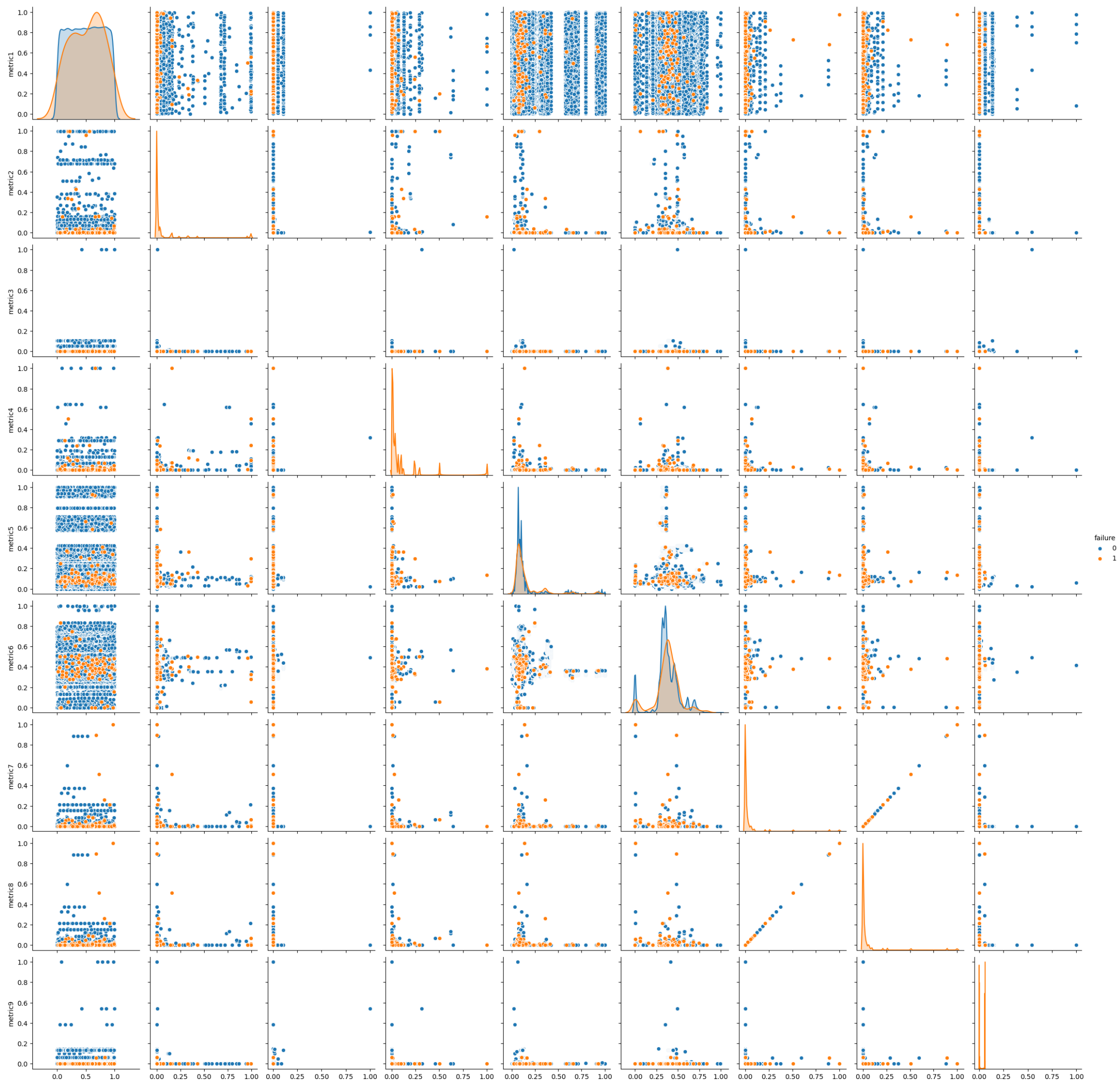
[111]:
```python
# Create figure and plot space
sns.set()
fig, ax = plt.subplots(figsize=(20, 5))

# Add x-axis and y-axis
ax.bar(df2.index.values, df2["failure"], color='Green', width=4.8)
```

```
# Set title and labels for axes
ax.set(xlabel="Date",
       ylabel="Failure",
       title="Maintanence Failure in 2015 Monthly")

# Rotate tick marks on x-axis
plt.setp(ax.get_xticklabels(), rotation=45)

plt.show()
```

2.2 Further EDA - STD and PCT_Change New Features

[109]:
```
# Normalized and visulization
# Normalization metric1 ~ metric9

import warnings
warnings.filterwarnings('ignore')

columns_to_normalize = df[['metric1', 'metric2', 'metric3', 'metric4',
       'metric5', 'metric6', 'metric7', 'metric8', 'metric9']]
column_maxes = columns_to_normalize.max()
column_mins = columns_to_normalize.min()
normalized_df = (columns_to_normalize - column_mins) / (column_maxes -
 ↪column_mins)
columns_data_ID = df[['device', 'failure', 'date_month', 'date_weekday']]
df_record = pd.concat([columns_data_ID, normalized_df], axis = 1)

sns.pairplot(df_record[['failure','metric1', 'metric2', 'metric3', 'metric4',
       'metric5', 'metric6', 'metric7', 'metric8', 'metric9']], hue='failure',
 ↪height=2.5)
```

[109]: <seaborn.axisgrid.PairGrid at 0x249c06ddcd0>



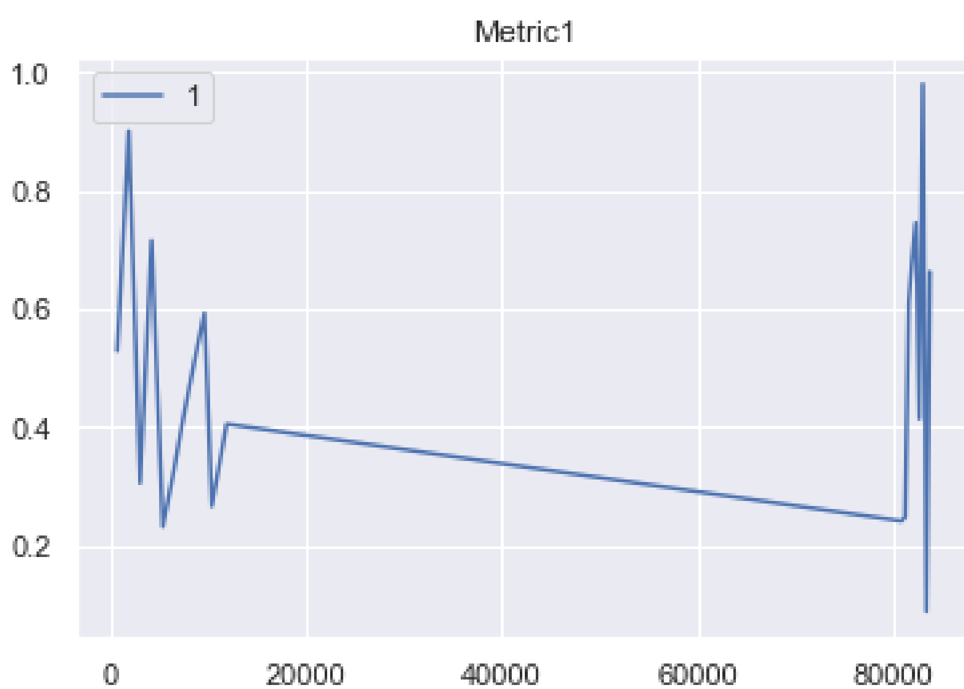
[22]:
```
# Data Exploratory
EDA = df[['device','failure','metric1', 'metric2', 'metric3', 'metric4',
        'metric5', 'metric6', 'metric7', 'metric8', 'metric9']]

device_name = df_record["device"].unique()

to_plot = {}
for device in device_name:
    x = df_record[df_record["device"] == device][['device', 'failure',␣
 ↪'metric1', 'metric2', 'metric3', 'metric4',
        'metric5', 'metric6', 'metric7', 'metric8', 'metric9']]
    if (len(x) > 1) & (x['failure'].sum() > 0):
            to_plot[device] = x
```

[23]:
```
to_plot.keys()
```

[23]:
```
dict_keys(['S1F023H2', 'S1F03YZM', 'S1F09DZQ', 'S1F0CTDN', 'S1F0DSTY',
'S1F0F4EB', 'S1F0GG8X', 'S1F0GJW3', 'S1F0GKFX', 'S1F0GKL6', 'S1F0GPFZ',
'S1F0GSD9', 'S1F0GSHB', 'S1F0J5JH', 'S1F0JD7P', 'S1F0JGJV', 'S1F0LODW',
'S1F0LCTV', 'S1F0LCVC', 'S1F0LD15', 'S1F0LD2C', 'S1F0P3G2', 'S1F0PJJW',
'S1F0QF3R', 'S1F0QY11', 'S1F0RR35', 'S1F0RRB1', 'S1F0RSZP', 'S1F0S2WJ',
'S1F0S4CA', 'S1F0S4EG', 'S1F0S4T6', 'S1F0S57T', 'S1F0S65X', 'S1F0T2LA',
'S1F0TQCV', 'S1F10E6M', 'S1F11MB0', 'S1F13589', 'S1F135TN', 'S1F136J0',
'S1F13H80', 'W1F03D4L', 'W1F03DP4', 'W1F08EDA', 'W1F0F6BN', 'W1F0FKWW',
'W1F0FW0S', 'W1F0GCAZ', 'W1F0KCP2', 'W1F0M35B', 'W1F0M4BZ', 'W1F0NZZZ',
'W1F0P114', 'W1F0PAXH', 'W1F0PNA5', 'W1F0Q8FH', 'W1F0SGHR', 'W1F0T034',
'W1F0T074', 'W1F0T0B1', 'W1F0TA59', 'W1F0VDH2', 'W1F0WBTM', 'W1F0X4FC',
'W1F0X5GW', 'W1F0Z1W9', 'W1F0Z3KR', 'W1F0Z4EA', 'W1F11ZG9', 'W1F1230J',
'W1F13SRV', 'W1F14XGD', 'W1F15S4D', 'W1F19BPT', 'W1F1BFP5', 'W1F1BS0H',
'W1F1BZTM', 'W1F1C9TE', 'W1F1C9WG', 'W1F1CB5E', 'W1F1CDDP', 'W1F1CJ1K',
'W1F1DQN8', 'Z1F04GCH', 'Z1F0B4XZ', 'Z1F0FSBY', 'Z1F0K451', 'Z1F0LSNZ',
'Z1F0LVGY', 'Z1F0LVPW', 'Z1F0MCCA', 'Z1F0MRPJ', 'Z1F0NVZA', 'Z1F0P16F',
'Z1F0P5D9', 'Z1F0QH0C', 'Z1F130LH', 'Z1F148T1', 'Z1F14BGY', 'Z1F1653X',
'Z1F1901P', 'Z1F1AG5N', 'Z1F1FCH5', 'Z1F1RJFA', 'Z1F1VQFY'])
```

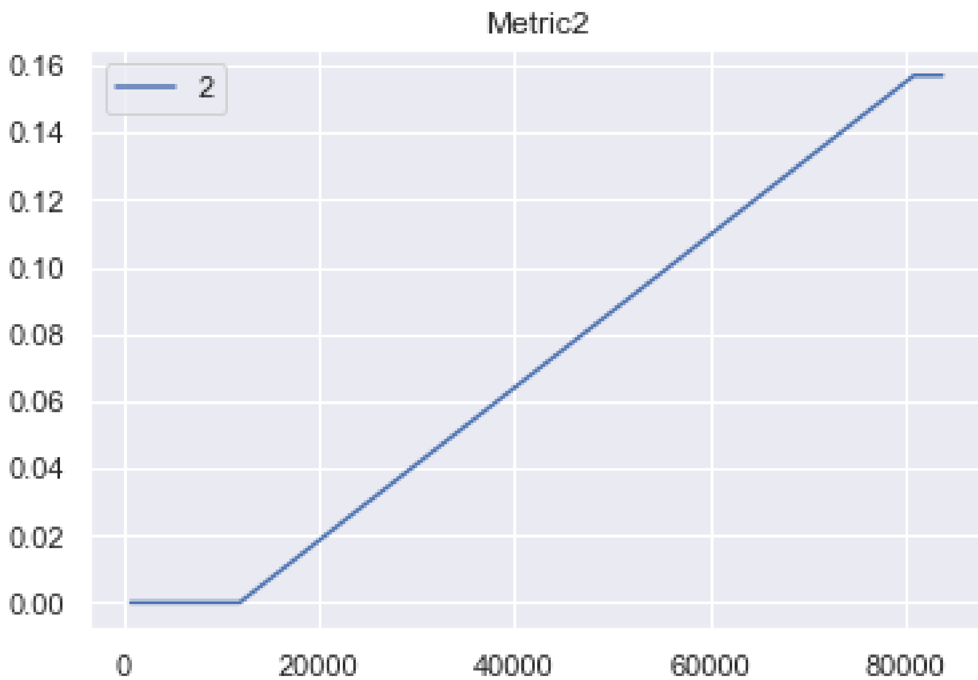
[32]:
```
sns.set()
to_plot['W1F0X5GW']["metric1"].plot().set_title("Metric1")
plt.legend('1', ncol=2, loc='upper left')
```

[32]: <matplotlib.legend.Legend at 0x249c5729880>



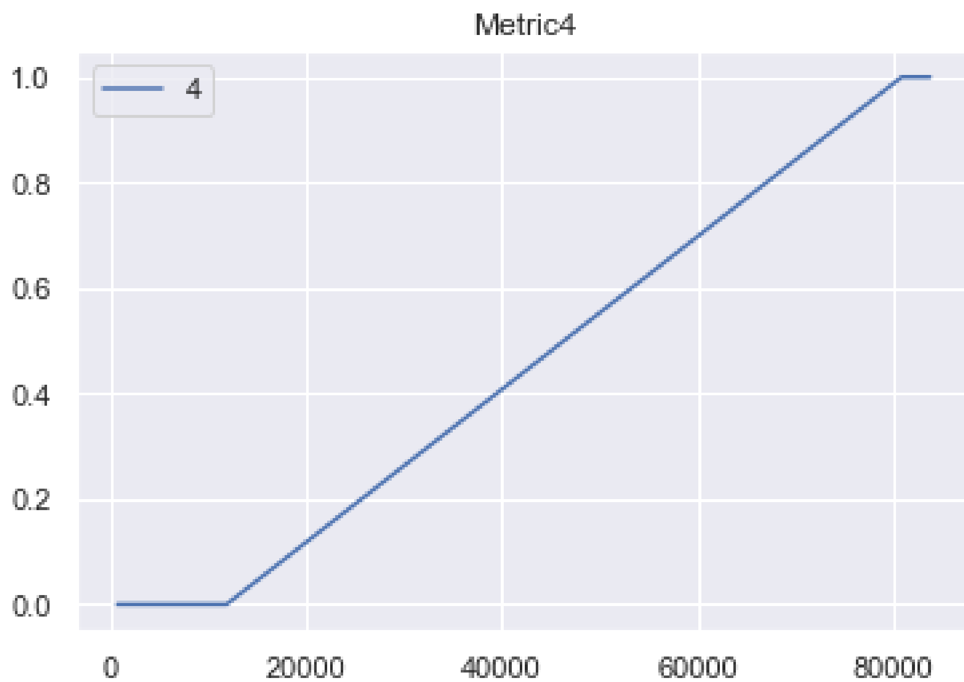
[41]:
```
sns.set()
to_plot['W1F0X5GW']["metric2"].plot().set_title("Metric2")
plt.legend('2', ncol=2, loc='upper left')
```

[41]: <matplotlib.legend.Legend at 0x249c6d59610>



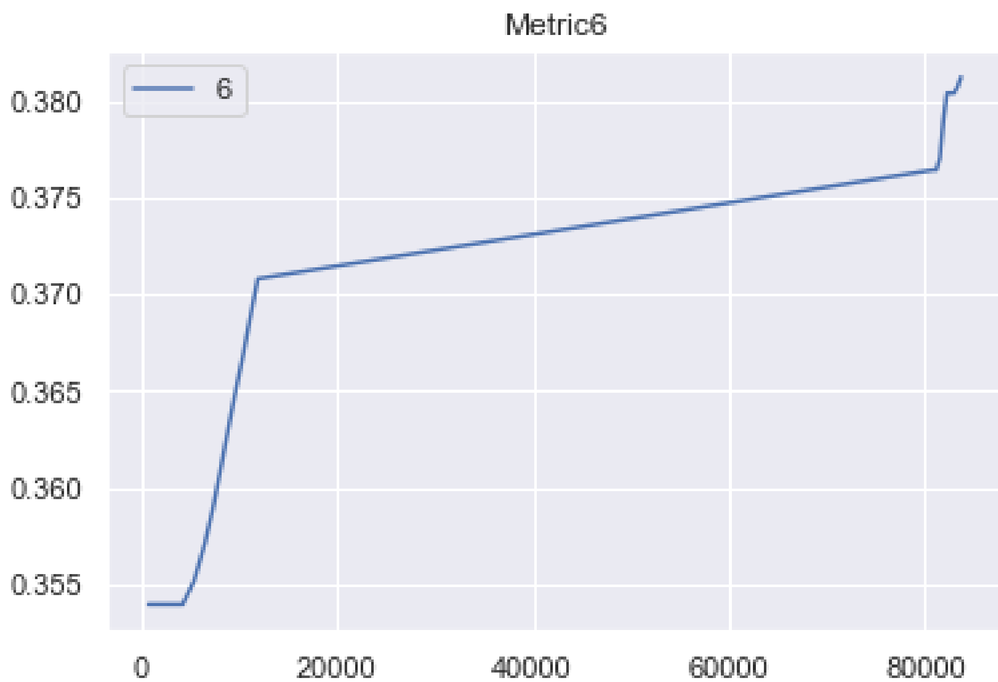
[42]:
```
sns.set()
to_plot['W1F0X5GW']["metric4"].plot().set_title("Metric4")
plt.legend('4', ncol=2, loc='upper left')
```

[42]: <matplotlib.legend.Legend at 0x249f245bca0>



[43]:
```
sns.set()
to_plot['W1F0X5GW']["metric6"].plot().set_title("Metric6")
plt.legend('6', ncol=2, loc='upper left')
```

[43]:
```
<matplotlib.legend.Legend at 0x249f252f760>
```



[110]:
```
# Create STD and PCT_Change columns for metric1, metric2, metric6

device_name = df_record["device"].unique()

def stdev(data):
    n = len(data)
    mean = sum(data) / n
    deviations = [(x - mean) ** 2 for x in data]
    variance = sum(deviations) / n
    std_dev = math.sqrt(variance)
    return std_dev

df_stack = pd.DataFrame(columns=['device', 'failure', 'metric1', 'metric2',␣
 ↪'metric3', 'metric4',
'metric5', 'metric6', 'metric7', 'metric8', 'metric9', 'date_month',␣
 ↪'date_weekday',
"metric1_std", "metric1_pct", "metric2_std", "metric2_pct","metric4_std",␣
 ↪"metric4_pct", "metric6_std", "metric6_pct"])

for device in device_name:
    data = df_record[df_record["device"] == device]
    data["metric1_std"] = stdev(data["metric1"])
    data["metric1_pct"] = data["metric1"].pct_change()
    data["metric2_std"] = stdev(data["metric2"])
```

```
    data["metric2_pct"] = data["metric2"].pct_change()
    data["metric4_std"] = stdev(data["metric4"])
    data["metric4_pct"] = data["metric4"].pct_change()
    data["metric6_std"] = stdev(data["metric6"])
    data["metric6_pct"] = data["metric6"].pct_change()
    df_stack = pd.concat([df_stack, data])

df_record = df_record.join(df_stack[["metric1_std", "metric1_pct",␣
 ↪"metric2_std", "metric2_pct","metric4_std", "metric4_pct", "metric6_std",␣
 ↪"metric6_pct"]], how='left')

impact_columns = ['metric1_pct','metric2_pct','metric4_pct','metric6_pct']
[df_record[col].replace(np.inf, 1, inplace=True) for col in impact_columns]
[df_record[col].replace(np.nan, 0, inplace=True) for col in impact_columns]
```

[110]:

```
[None, None, None, None]
```

[108]:

```
df_record.head()
```

[108]:

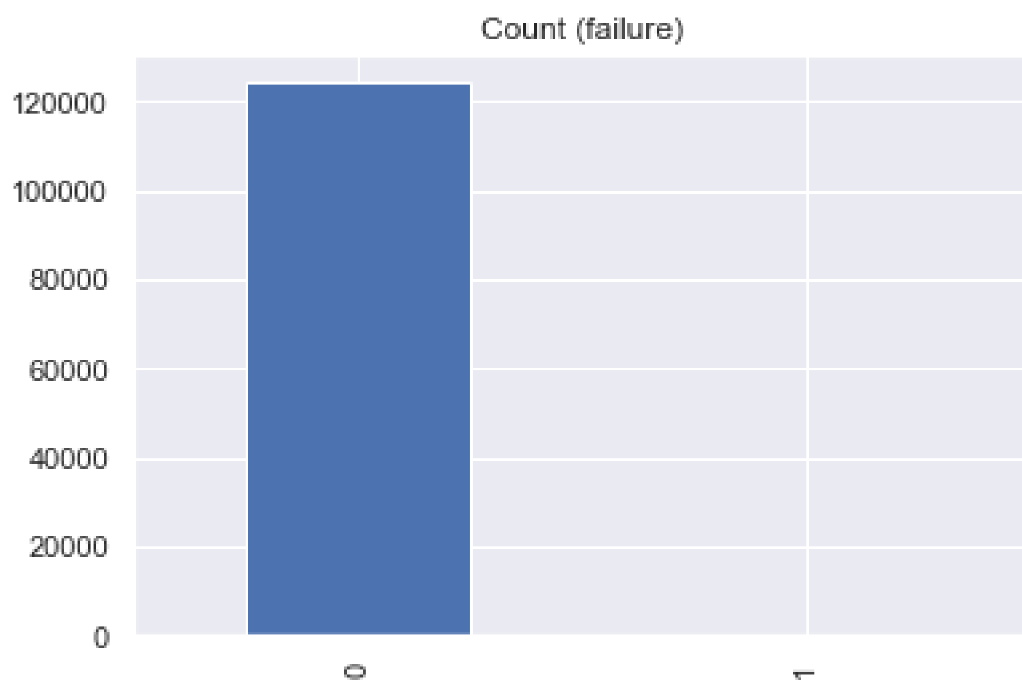
```
     device  failure  date_month  date_weekday   metric1   metric2  metric3  \
0  S1F01085        0           1             3  0.883224  0.000862  0.00000
1  S1F0166B        0           1             3  0.251374  0.000000  0.00012
2  S1F01E6Y        0           1             3  0.709821  0.000000  0.00000
3  S1F01JE0        0           1             3  0.326427  0.000000  0.00000
4  S1F01R2B        0           1             3  0.556935  0.000000  0.00000

    metric4   metric5   metric6  ...  metric8   metric9  metric1_std  \
0  0.031212  0.051546  0.591204  ...      0.0  0.000374     0.257554
1  0.000000  0.051546  0.585017  ...      0.0  0.000000     0.310377
2  0.000000  0.113402  0.344461  ...      0.0  0.000000     0.276362
3  0.000000  0.051546  0.595191  ...      0.0  0.000000     0.240849
4  0.000000  0.144330  0.454420  ...      0.0  0.000160     0.277976

   metric1_pct   metric2_std  metric2_pct   metric4_std  metric4_pct  \
0          0.0  1.084202e-19          0.0  3.469447e-18          0.0
1          0.0  0.000000e+00          0.0  0.000000e+00          0.0
2          0.0  0.000000e+00          0.0  0.000000e+00          0.0
3          0.0  0.000000e+00          0.0  0.000000e+00          0.0
4          0.0  0.000000e+00          0.0  0.000000e+00          0.0

   metric6_std  metric6_pct
0     0.001053          0.0
1     0.000871          0.0
2     0.009542          0.0
3     0.001054          0.0
4     0.006854          0.0
```

```
[5 rows x 21 columns]
```

2.3 Train/test split

[47]:
```
# Investigation
target_count = df_record.failure.value_counts()
print('Class 0:', target_count[0])
print('Class 1:', target_count[1])
print('Proportion:', round(target_count[0] / target_count[1], 2), ': 1')

target_count.plot(kind='bar', title='Count (failure)');
```

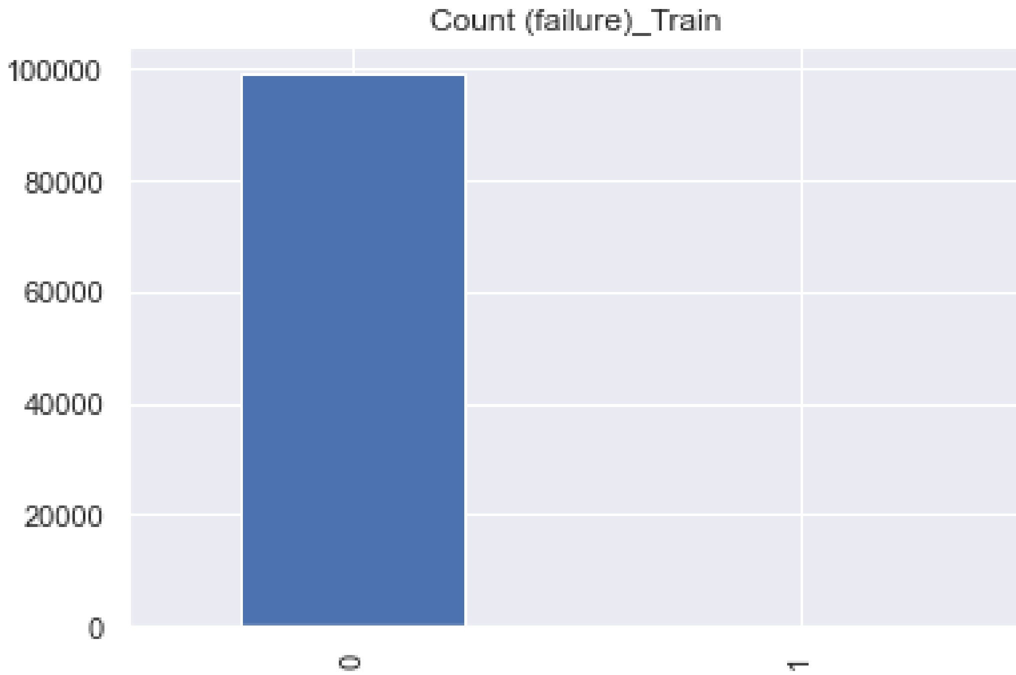
```
Class 0: 124388
Class 1: 106
Proportion: 1173.47 : 1
```



[48]:
```
# GroupShuffleSplit
from sklearn.model_selection import GroupShuffleSplit

train_inds, test_inds = next(GroupShuffleSplit(test_size=.20, n_splits=2,␣
↪random_state = 7).split(df_record[['metric1', 'metric2', 'metric3', 'metric4',
       'metric5', 'metric6', 'metric7', 'metric8', 'metric9', 'date_month',
       'date_weekday', 'metric1_std', 'metric1_pct', 'metric2_std',␣
↪'metric2_pct',
```

```
       'metric4_std', 'metric4_pct','metric6_std', 'metric6_pct']],␣
↪groups=df_record['device']))

train_X = df_record.iloc[train_inds][['metric1', 'metric2', 'metric3', 'metric4',
       'metric5', 'metric6', 'metric7', 'metric8', 'metric9', 'date_month',
       'date_weekday', 'metric1_std', 'metric1_pct', 'metric2_std',␣
↪'metric2_pct',
       'metric4_std', 'metric4_pct','metric6_std', 'metric6_pct']]

train_y = df_record.iloc[train_inds]['failure']

test_X = df_record.iloc[test_inds][['metric1', 'metric2', 'metric3', 'metric4',
       'metric5', 'metric6', 'metric7', 'metric8', 'metric9', 'date_month',
       'date_weekday', 'metric1_std', 'metric1_pct', 'metric2_std',␣
↪'metric2_pct',
       'metric4_std', 'metric4_pct', 'metric6_std', 'metric6_pct']]

test_y = df_record.iloc[test_inds]['failure']
train_y = train_y.astype('int')
test_y = test_y.astype('int')

# Investigation
target_count = train_y.value_counts()
print('Class 0:', target_count[0])
print('Class 1:', target_count[1])
print('Proportion:', round(target_count[0] / target_count[1], 2), ': 1')

target_count.plot(kind='bar', title='Count (failure)_Train');
```

```
Class 0: 99219
Class 1: 88
Proportion: 1127.49 : 1
```



[49]:
```
# Random Train_Test_Split

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(df_record[['metric1',␣
↪'metric2', 'metric3', 'metric4',
       'metric5', 'metric6', 'metric7', 'metric8', 'metric9', 'date_month',
       'date_weekday', 'metric1_std', 'metric1_pct', 'metric2_std',
       'metric2_pct', 'metric4_std', 'metric4_pct', 'metric6_std',␣
↪'metric6_pct']].values, df_record.failure.values, test_size=0.15, random_state␣
↪= 7)

X_train = pd.DataFrame(X_train, columns = ['metric1', 'metric2', 'metric3',␣
↪'metric4',
       'metric5', 'metric6', 'metric7', 'metric8', 'metric9', 'date_month',
       'date_weekday', 'metric1_std', 'metric1_pct', 'metric2_std',
       'metric2_pct', 'metric4_std', 'metric4_pct', 'metric6_std',␣
↪'metric6_pct'])

X_test = pd.DataFrame(X_test, columns = ['metric1', 'metric2', 'metric3',␣
↪'metric4',
       'metric5', 'metric6', 'metric7', 'metric8', 'metric9', 'date_month',
       'date_weekday', 'metric1_std', 'metric1_pct', 'metric2_std',
```

```
        'metric2_pct', 'metric4_std', 'metric4_pct', 'metric6_std',␣
 ↪'metric6_pct'])

y_train = y_train.astype('int')
y_test = y_test.astype('int')

y_train = pd.Series(y_train)
y_test = pd.Series(y_test)

y_train.name = "failure"
y_test.name = "failure"

# Investigation
target_count = y_train.value_counts()
print('Class 0:', target_count[0])
print('Class 1:', target_count[1])
print('Proportion:', round(target_count[0] / target_count[1], 2), ': 1')

target_count.plot(kind='bar', title='Count (failure)_Train');
```

```
Class 0: 105732
Class 1: 87
Proportion: 1215.31 : 1
```

2.4 Imbalanced process - upsampling

[50]:
```
import imblearn
from collections import Counter

X = train_X
y = train_y
counter = Counter(y)
print(counter)

def plot_2d_space(X, y, label='Classes'):
    colors = ['#1F77B4', '#FF7F0E']
    markers = ['o', 's']
    for l, c, m in zip(np.unique(y), colors, markers):
        plt.scatter(
            X[y==l, 0],
            X[y==l, 1],
            c=c, label=l, marker=m
        )
    plt.title(label)
    plt.legend(loc='upper right')
    plt.show()
```

```
Counter({0: 99219, 1: 88})
```

[ ]:
```
# Method 1 - Upsampling all - Random
from imblearn.over_sampling import RandomOverSampler

ros = RandomOverSampler()
X_ros, y_ros = ros.fit_resample(X, y)
train_resample= X_ros.join(y_ros, how='left')

print(X_ros.shape[0] - X.shape[0], 'new random picked points')

# plot_2d_space(X_ros, y_ros, 'Random over-sampling')

train_resample_X = X_ros
train_resample_y = y_ros
```

[ ]:
```
# Method 2 - Upsampling all - SMOTE
from imblearn.over_sampling import SMOTE

smote = SMOTE(sampling_strategy=1, random_state=7)
X_sm, y_sm = smote.fit_resample(X, y)
train_resample= X_sm.join(y_sm, how='left')

counter = Counter(y_sm)
print(counter)
```

```
# plot_2d_space(X_sm, y_sm, 'SMOTE over-sampling')

train_resample_X = X_sm
train_resample_y = y_sm
```

[107]:
```
# Method 3 - Upsampling on device basis
from imblearn.over_sampling import SMOTE
from imblearn.over_sampling import RandomOverSampler

device_name = df_record["device"].unique()

df_over_sampling_X = pd.DataFrame(columns=['metric1', 'metric2', 'metric3',␣
 ↪'metric4',
       'metric5', 'metric6', 'metric7', 'metric8', 'metric9', 'date_month',
       'date_weekday', 'metric1_std', 'metric1_pct', 'metric2_std',
       'metric2_pct', 'metric4_std', 'metric4_pct', 'metric6_std',␣
 ↪'metric6_pct'])
df_over_sampling_y = pd.DataFrame(columns=['failure'])
n_new_rows = 0

for device in device_name:
    data = df_record[df_record["device"] == device]
    X_single = data[['device','metric1', 'metric2', 'metric3', 'metric4',
       'metric5', 'metric6', 'metric7', 'metric8', 'metric9', 'date_month',
       'date_weekday', 'metric1_std', 'metric1_pct', 'metric2_std',␣
 ↪'metric2_pct','metric4_std', 'metric4_pct', 'metric6_std', 'metric6_pct']]
    y_single = pd.DataFrame(data['failure'], columns = ['failure'])
    if len(data['failure'].unique()) == 2:
        ros = RandomOverSampler()
        X_ros, y_ros = ros.fit_resample(X_single, y_single)
        n_new_rows += X_ros.shape[0] - X_single.shape[0]

        df_over_sampling_X = pd.concat([df_over_sampling_X, X_ros])
        df_over_sampling_y = pd.concat([df_over_sampling_y, y_ros])
    else:
        df_over_sampling_X = pd.concat([df_over_sampling_X, X_single])
        df_over_sampling_y = pd.concat([df_over_sampling_y, y_single])

print("n_new_rows", n_new_rows)
train_resample= pd.concat([df_over_sampling_X,df_over_sampling_y], axis = 1)

train_resample_X = df_over_sampling_X[['metric1', 'metric2', 'metric3',␣
 ↪'metric4',
       'metric5', 'metric6', 'metric7', 'metric8', 'metric9', 'date_month',
       'date_weekday', 'metric1_std', 'metric1_pct', 'metric2_std',
       'metric2_pct', 'metric4_std', 'metric4_pct', 'metric6_std',␣
 ↪'metric6_pct']]
```

```
train_resample_y = df_over_sampling_y.astype('int')
```

```
n_new_rows 10501
```

3 Modelling

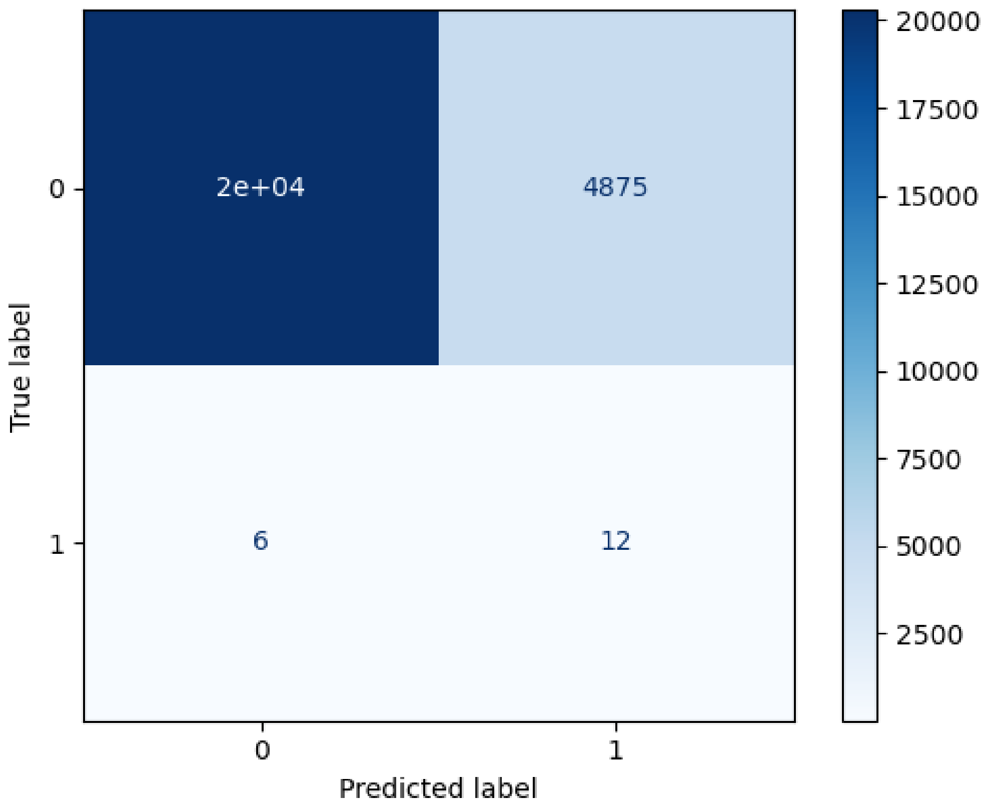
3.1 Logistic Regression

[83]:
```
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (2, 2)
plt.style.use('default')
```

[84]:
```
# Logistic Regression Model - Shuffle

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import precision_score, recall_score, f1_score,␣
 ↪matthews_corrcoef
from sklearn.metrics import precision_recall_curve, roc_curve, auc, roc_auc_score
from sklearn.preprocessing import label_binarize
from sklearn.metrics import classification_report

LR = LogisticRegression(max_iter=1000, class_weight='balanced')
# Fit the model on the trainng data.
LR.fit(train_resample_X, train_resample_y.values.ravel())

# Print the accuracy, precision, recall from the testing data.
print("Accuracy: ", accuracy_score(test_y, LR.predict(test_X)))
print("Precision: ", precision_score(test_y, LR.predict(test_X)))
print("Recall: ", recall_score(test_y, LR.predict(test_X)))
print("F1 score: ", f1_score(test_y, LR.predict(test_X)))
print("MCC score: ", matthews_corrcoef(test_y, LR.predict(test_X)))
print(classification_report(test_y, LR.predict(test_X), target_names=['Class 0␣
 ↪Sucess:', 'Class 1 Fail:']))

# Plot Confusion Matrix
print("Confusion matrix: ", confusion_matrix(test_y, LR.predict(test_X)))
cm=confusion_matrix(test_y, LR.predict(test_X))
plot_confusion_matrix(LR, test_X, test_y, cmap=plt.cm.Blues)
plt.show()
```

```
Accuracy:  0.8062095525469488
Precision:  0.0024554941682013503
Recall:  0.6666666666666666
F1 score:  0.004892966360856269
```

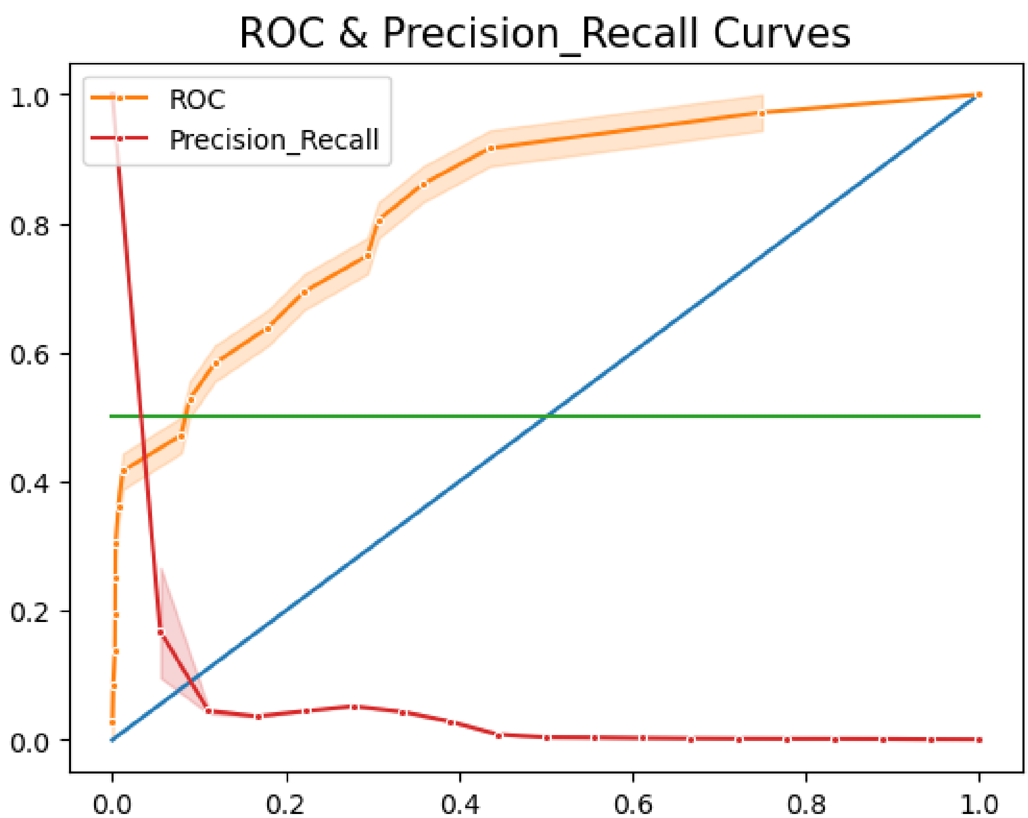
```
MCC score:  0.03196238384478931
                  precision    recall  f1-score   support

Class 0 Sucess:       1.00      0.81      0.89     25169
  Class 1 Fail:       0.00      0.67      0.00        18

       accuracy                           0.81     25187
      macro avg       0.50      0.74      0.45     25187
   weighted avg       1.00      0.81      0.89     25187

Confusion matrix:  [[20294  4875]
 [    6    12]]
```



[85]:
```python
# Plot ROC Curve - Shuffle
probs = LR.predict_proba(test_X)
probs = probs[:,1]
fpr, tpr, thresholds = roc_curve(test_y, probs)
sns.lineplot([0,1], [0, 1], linestyle="--")
plt = sns.lineplot(fpr, tpr, marker = ".", legend='full', label=str("ROC"))
plt.set_title("ROC & Precision_Recall Curves", fontsize=15)
auc_score = roc_auc_score(test_y, probs)
```

```
print("AUC_ROC: %.3f" % auc_score)

# Plot Precision/Recall Curve
probs = LR.predict_proba(test_X)
probs = probs[:,1]
precision, recall, thresholds = precision_recall_curve(test_y, probs)
sns.lineplot([0,1], [0.5, 0.5], linestyle="--")
plt = sns.lineplot(recall, precision, marker = ".", legend='full',␣
 ↪label=str("Precision_Recall"))
pr_auc_score = auc(recall, precision)
print("AUC_PR: %.3f" % pr_auc_score)
```

```
AUC_ROC: 0.841
AUC_PR: 0.074
```



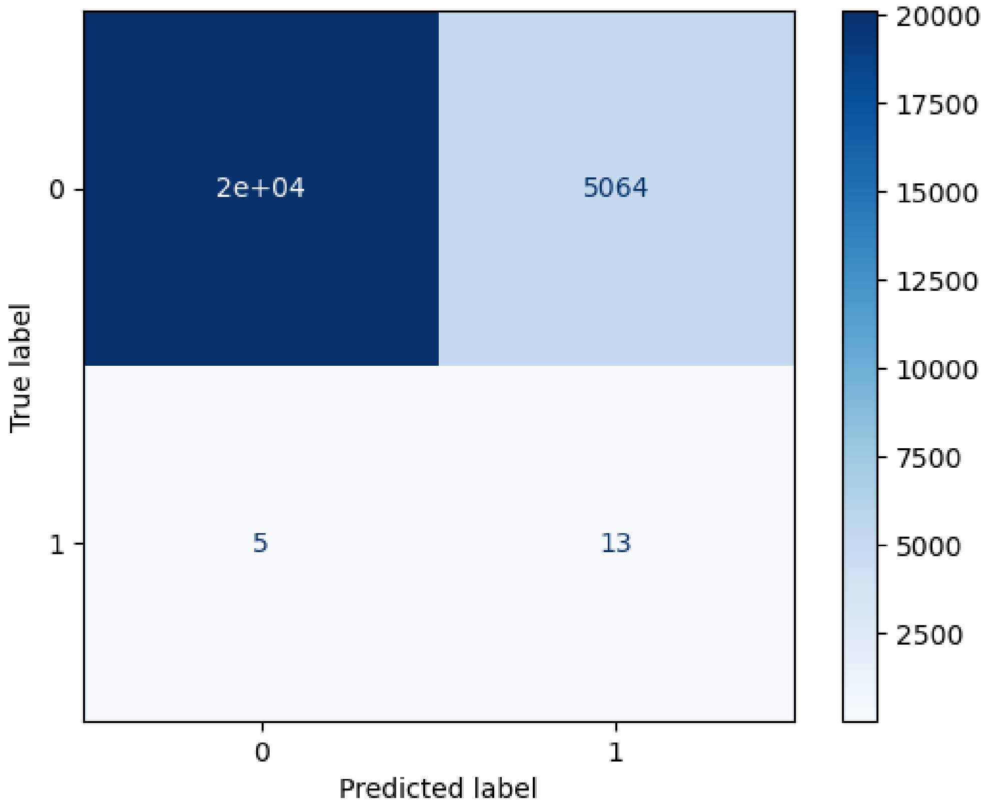
3.2 SVM Model

[97]:
```
# SVM Model - Shuffle
from sklearn.svm import SVC
from sklearn import preprocessing
```

```python
SVC = SVC(kernel='linear', class_weight='balanced', probability=True)

# Fit the model on the trainng data.
SVC.fit(train_resample_X, train_resample_y.values.ravel())

pred_y = SVC.predict(test_X)
# Print the accuracy, precision, recall from the testing data.
print("Accuracy: ", accuracy_score(test_y, pred_y))
print("Precision: ", precision_score(test_y, pred_y))
print("Recall: ", recall_score(test_y, pred_y))
print("F1 score: ", f1_score(test_y, pred_y))
print("MCC score: ", matthews_corrcoef(test_y, pred_y))
print(classification_report(test_y, pred_y, target_names=['Class 0 Sucess:',␣
 ↪'Class 1 Fail:']))

# Plot Confusion Matrix
import matplotlib.pyplot as plt
print("Confusion matrix: ", confusion_matrix(test_y, pred_y))
cm=confusion_matrix(test_y, pred_y)
plt.clf()
plot_confusion_matrix(SVC, test_X, test_y, cmap=plt.cm.Blues)
plt.show()
```

```
Accuracy:  0.7987453845237622
Precision:  0.0025605672641323615
Recall:  0.7222222222222222
F1 score:  0.005103042198233562
MCC score:  0.03470691047367835
                 precision    recall  f1-score   support

Class 0 Sucess:       1.00      0.80      0.89     25169
  Class 1 Fail:       0.00      0.72      0.01        18

       accuracy                           0.80     25187
      macro avg       0.50      0.76      0.45     25187
   weighted avg       1.00      0.80      0.89     25187

Confusion matrix:  [[20105  5064]
 [    5    13]]
```

```
<Figure size 640x480 with 0 Axes>
```

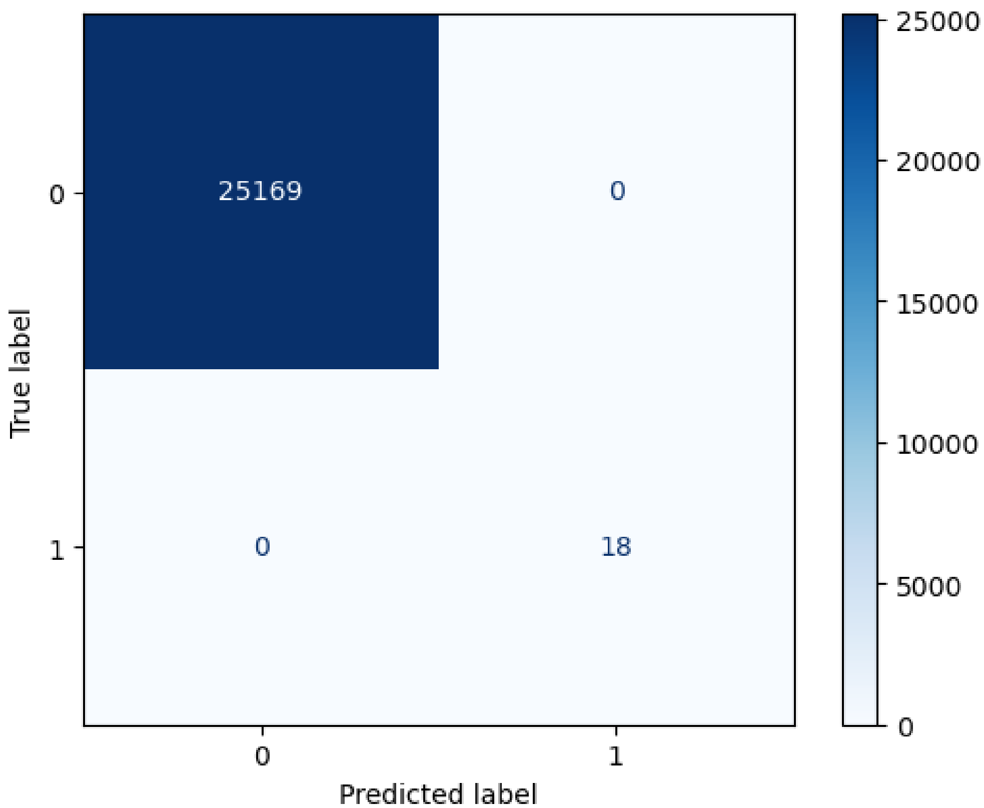


3.3 Random Forest Model

[86]:
```
# Random Forest Model - Ruffle

from sklearn.ensemble import RandomForestClassifier

RF = RandomForestClassifier(n_estimators=10)

# Train
RF.fit(train_resample_X, train_resample_y.values.ravel())
# Extract single tree
estimator = RF.estimators_[5]

# Print the accuracy, precision, recall from the testing data.
print("Accuracy: ", accuracy_score(test_y, RF.predict(test_X)))
print("Precision: ", precision_score(test_y, RF.predict(test_X)))
print("Recall: ", recall_score(test_y, RF.predict(test_X)))
print("F1 score: ", f1_score(test_y, RF.predict(test_X)))
print("MCC score: ", matthews_corrcoef(test_y, RF.predict(test_X)))
```

```
print(classification_report(test_y, RF.predict(test_X), target_names=['Class 0␣
↪Sucess:', 'Class 1 Fail:']))

# Plot Confusion Matrix
print("Confusion matrix: ", confusion_matrix(test_y, RF.predict(test_X)))
cm=confusion_matrix(test_y, RF.predict(test_X))
plot_confusion_matrix(RF, test_X, test_y, cmap=plt.cm.Blues)
plt.show()
```

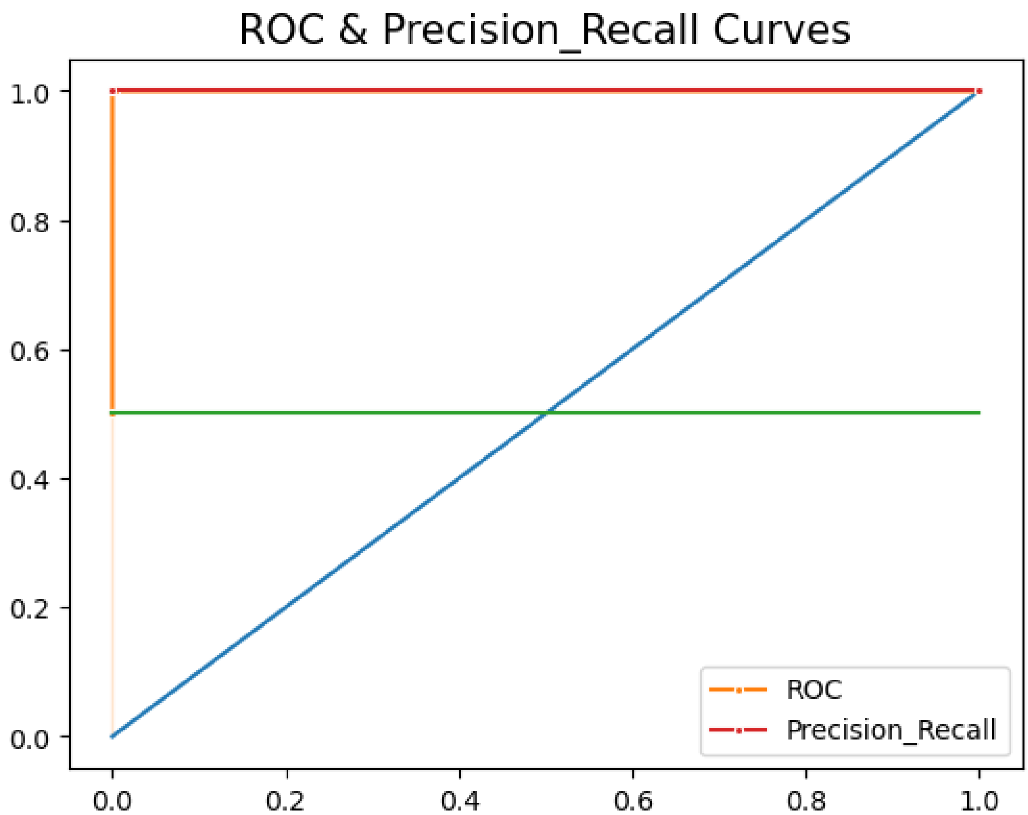
```
Accuracy:  1.0
Precision:  1.0
Recall:  1.0
F1 score:  1.0
MCC score:  1.0
                 precision    recall  f1-score   support

Class 0 Sucess:       1.00      1.00      1.00     25169
  Class 1 Fail:       1.00      1.00      1.00        18

       accuracy                           1.00     25187
      macro avg       1.00      1.00      1.00     25187
   weighted avg       1.00      1.00      1.00     25187

Confusion matrix:  [[25169     0]
 [    0    18]]
```



[87]:
```
# Plot ROC Curve - Ruffle
probs = RF.predict_proba(test_X)
probs = probs[:,1]
fpr, tpr, thresholds = roc_curve(test_y, probs)
sns.lineplot([0,1], [0, 1], linestyle="--")
plt = sns.lineplot(fpr, tpr, marker = ".", legend='full', label=str("ROC"))
plt.set_title("ROC & Precision_Recall Curves", fontsize=15)
auc_score = roc_auc_score(test_y, probs)
print("AUC: %.3f" % auc_score)

# Plot Precision/Recall Curve
probs = RF.predict_proba(test_X)
probs = probs[:,1]
precision, recall, thresholds = precision_recall_curve(test_y, probs)
sns.lineplot([0,1], [0.5, 0.5], linestyle="--")
plt = sns.lineplot(recall, precision, marker = ".", legend='full',␣
↪label=str("Precision_Recall"))
pr_auc_score = auc(recall, precision)
print("AUC: %.3f" % pr_auc_score)
```

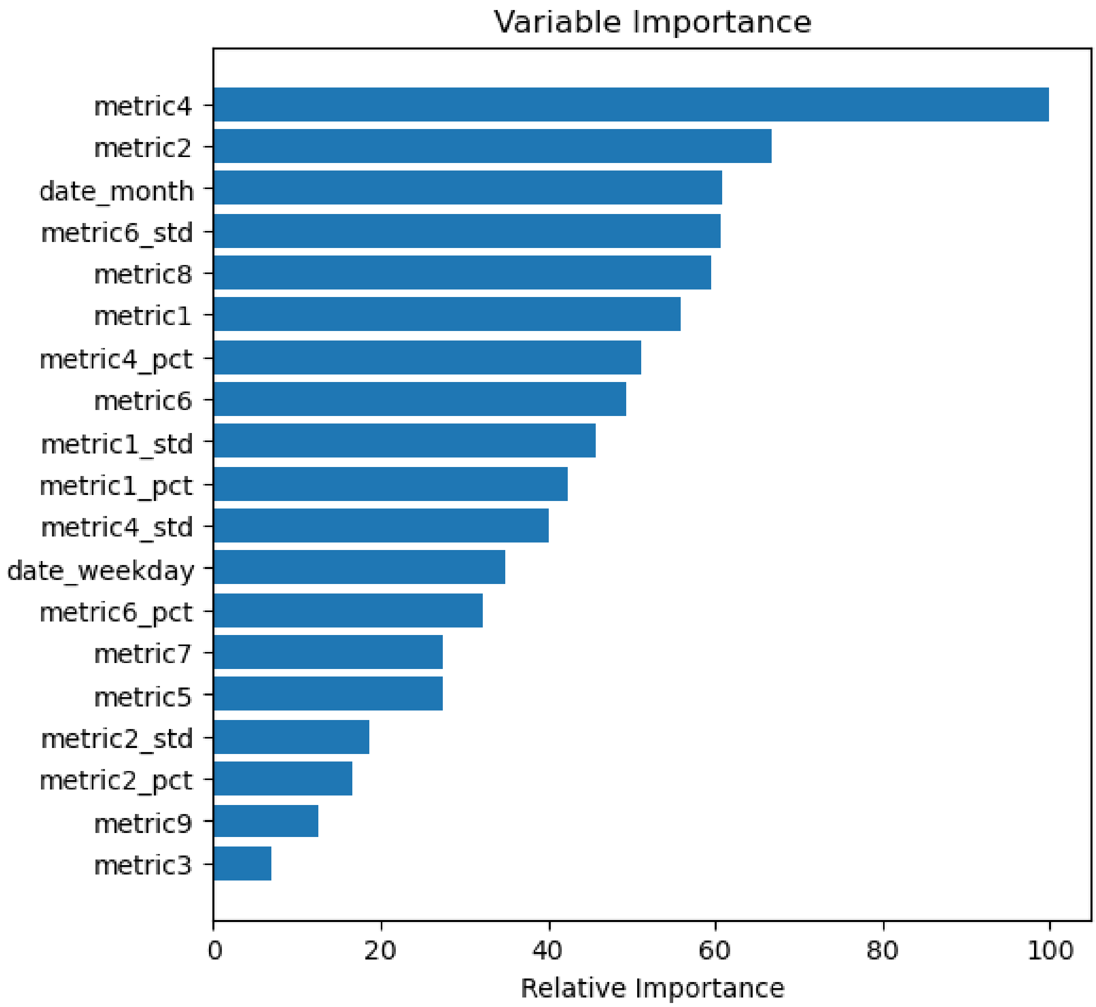
```
AUC: 1.000
```

AUC: 1.000



[90]:
```
import matplotlib.pyplot as plt

feature_importance = RF.feature_importances_
# make importances relative to max importance
feature_importance = 100.0 * (feature_importance / feature_importance.max())[:30]
sorted_idx = np.argsort(feature_importance)[:30]

pos = np.arange(sorted_idx.shape[0]) + .5
print(pos.size)
sorted_idx.size
plt.figure(figsize=(6,6))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X.columns[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```

19

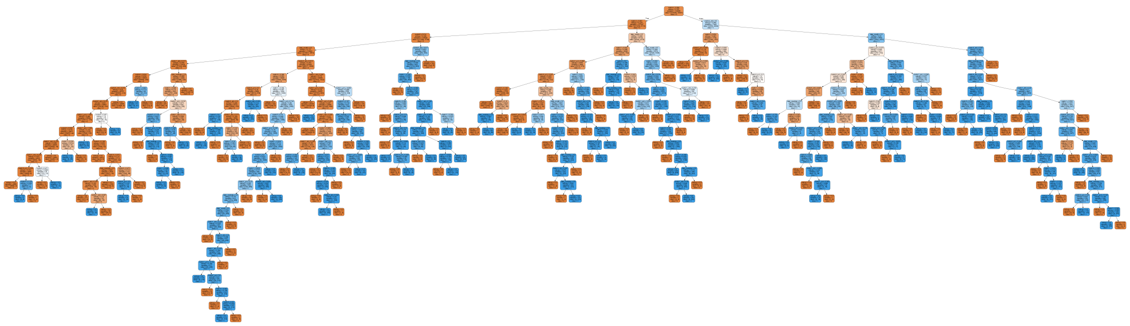


3.4 Decision Tree Model

[94]:
```
import os
os.environ["PATH"] += os.pathsep + 'C:\Program Files (x86)\Graphviz2.38/bin/'
import graphviz
from six import StringIO
from IPython.display import Image
from sklearn.tree import export_graphviz
import pydotplus
from sklearn import tree

# Now we want to visualize the tree
dot_data = StringIO()

# We can do so with export_graphviz
```

```
tree.export_graphviz(DT, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True, feature_names=train_X.
 ↪columns,class_names = ["0", "1"])

# Alternatively for class_names use entr_model.classes_
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```

[94]:

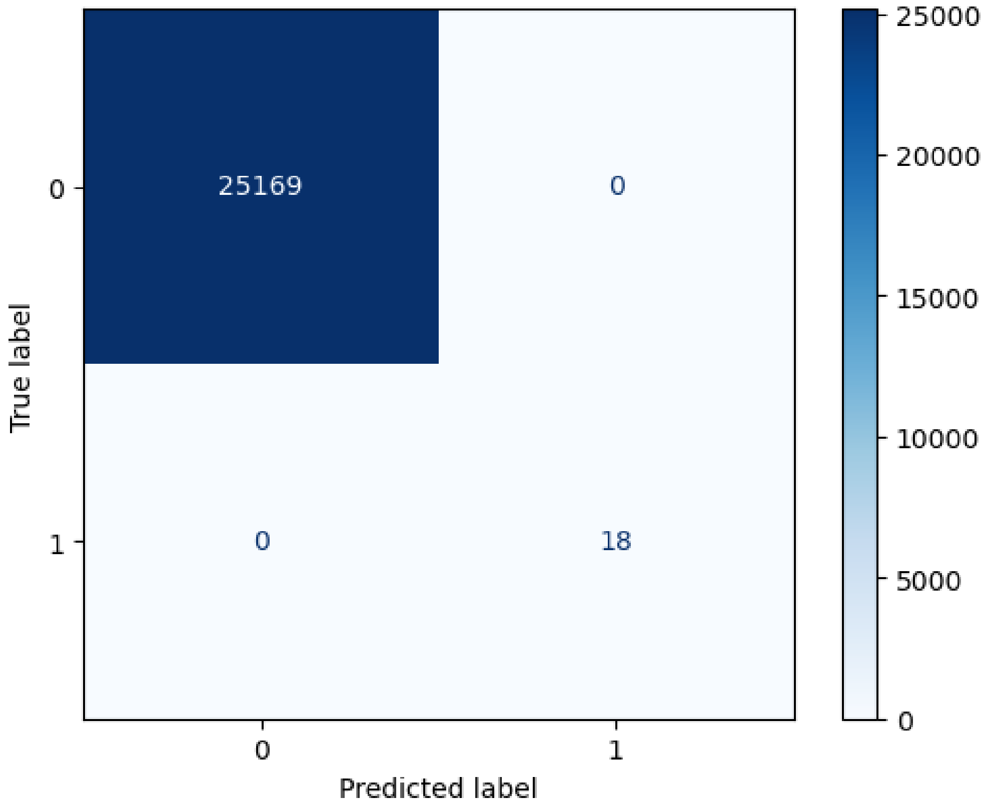


[93]:

```
# Decision Tree Model - Ruffle

from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
import matplotlib.pyplot as plt

DT = tree.DecisionTreeClassifier(criterion="entropy", random_state = 7)

# Train
DT.fit(train_resample_X, train_resample_y.values.ravel())

# Print the accuracy, precision, recall from the testing data.
print("Model Entropy - no max depth")
print("Accuracy: ", accuracy_score(test_y, DT.predict(test_X)))
print("Balanced accuracy:", balanced_accuracy_score(test_y, DT.predict(test_X)))
print("Precision for Normal: ", precision_score(test_y, DT.predict(test_X),␣
 ↪pos_label = 0))
print("Precision for Failure: ", precision_score(test_y, DT.predict(test_X),␣
 ↪pos_label = 1))
print("Recall for Normal: ", recall_score(test_y, DT.predict(test_X), pos_label␣
 ↪= 0))
print("Recall for Failure: ", recall_score(test_y, DT.predict(test_X), pos_label␣
 ↪= 1))
print("F1 score: ", f1_score(test_y, DT.predict(test_X)))
print("MCC score: ", matthews_corrcoef(test_y, DT.predict(test_X)))
```

```
print(classification_report(test_y, DT.predict(test_X), target_names=['Class 0␣
↪Sucess:', 'Class 1 Fail:']))

# Plot Confusion Matrix
print("Confusion matrix: ", confusion_matrix(test_y, DT.predict(test_X)))
cm=confusion_matrix(test_y, DT.predict(test_X))
plot_confusion_matrix(DT, test_X, test_y, cmap=plt.cm.Blues)
plt.show()
```

```
Model Entropy - no max depth
Accuracy:  1.0
Balanced accuracy: 1.0
Precision for Normal:  1.0
Precision for Failure:  1.0
Recall for Normal:  1.0
Recall for Failure:  1.0
F1 score:  1.0
MCC score:  1.0
                 precision    recall  f1-score   support

Class 0 Sucess:       1.00      1.00      1.00     25169
  Class 1 Fail:       1.00      1.00      1.00        18

       accuracy                           1.00     25187
      macro avg       1.00      1.00      1.00     25187
   weighted avg       1.00      1.00      1.00     25187

Confusion matrix:  [[25169     0]
 [    0    18]]
```

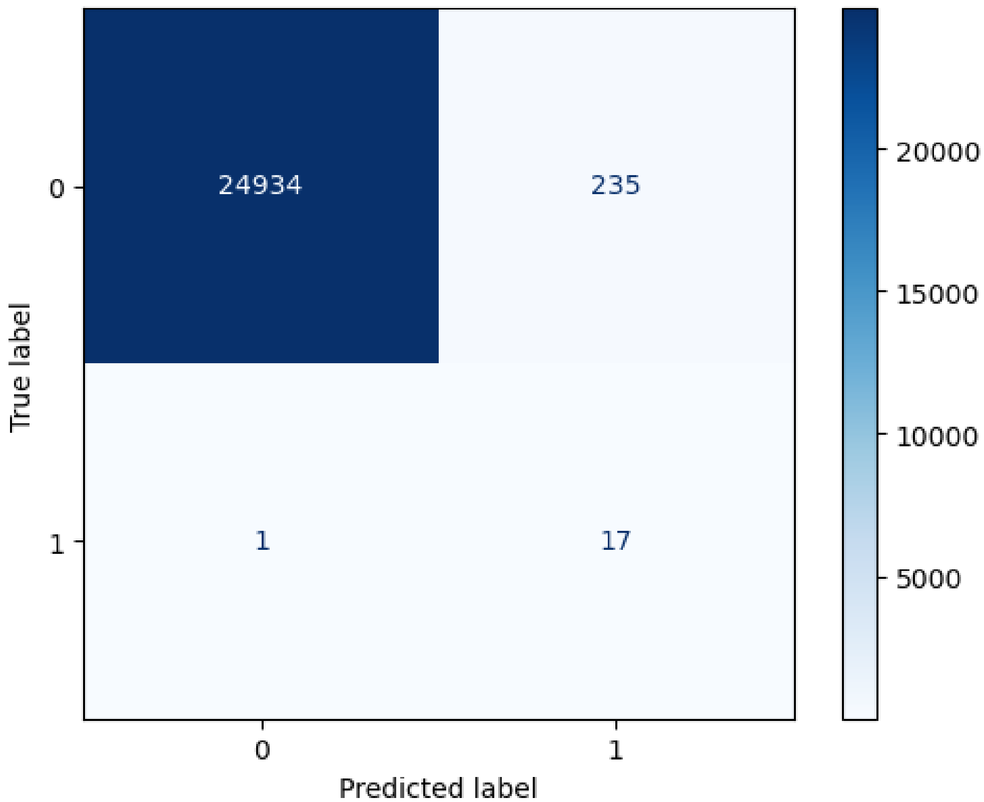


3.5 Deep Learning Model - Neural Network

[95]:
```
from sklearn.neural_network import MLPClassifier

MLP = MLPClassifier(max_iter=1000,␣
 ↪hidden_layer_sizes=(12,6),activation="logistic",random_state = 7)
MLP.fit(train_resample_X, train_resample_y.values.ravel())
y_pred=MLP.predict(test_X)
print(MLP.score(test_X, test_y))

print("Accuracy: ", accuracy_score(test_y, MLP.predict(test_X)))
print("Balanced accuracy:", balanced_accuracy_score(test_y, MLP.predict(test_X)))
print("Precision for Normal: ", precision_score(test_y, MLP.predict(test_X),␣
 ↪pos_label = 0))
print("Precision for Failure: ", precision_score(test_y, MLP.predict(test_X),␣
 ↪pos_label = 1))
print("Recall for Normal: ", recall_score(test_y, MLP.predict(test_X), pos_label␣
 ↪= 0))
print("Recall for Failure: ", recall_score(test_y, MLP.predict(test_X),␣
 ↪pos_label = 1))
```

```
print("F1 score: ", f1_score(test_y, MLP.predict(test_X)))
print("MCC score: ", matthews_corrcoef(test_y, MLP.predict(test_X)))
print(classification_report(test_y, MLP.predict(test_X), target_names=['Class 0␣
↪Sucess:', 'Class 1 Fail:']))

# Plot Confusion Matrix
print("Confusion matrix: ", confusion_matrix(test_y, MLP.predict(test_X)))
cm=confusion_matrix(test_y, MLP.predict(test_X))
plot_confusion_matrix(MLP, test_X, test_y, cmap=plt.cm.Blues)
plt.show()
```

```
0.9906300869496169
Accuracy:  0.9906300869496169
Balanced accuracy: 0.9675537808856574
Precision for Normal:  0.9999598957288951
Precision for Failure:  0.06746031746031746
Recall for Normal:  0.9906631173268704
Recall for Failure:  0.9444444444444444
F1 score:  0.1259259259259259
MCC score:  0.2510879351332254
                 precision    recall  f1-score   support

Class 0 Sucess:       1.00      0.99      1.00     25169
  Class 1 Fail:       0.07      0.94      0.13        18

       accuracy                           0.99     25187
      macro avg       0.53      0.97      0.56     25187
   weighted avg       1.00      0.99      0.99     25187

Confusion matrix:  [[24934   235]
 [    1    17]]
```

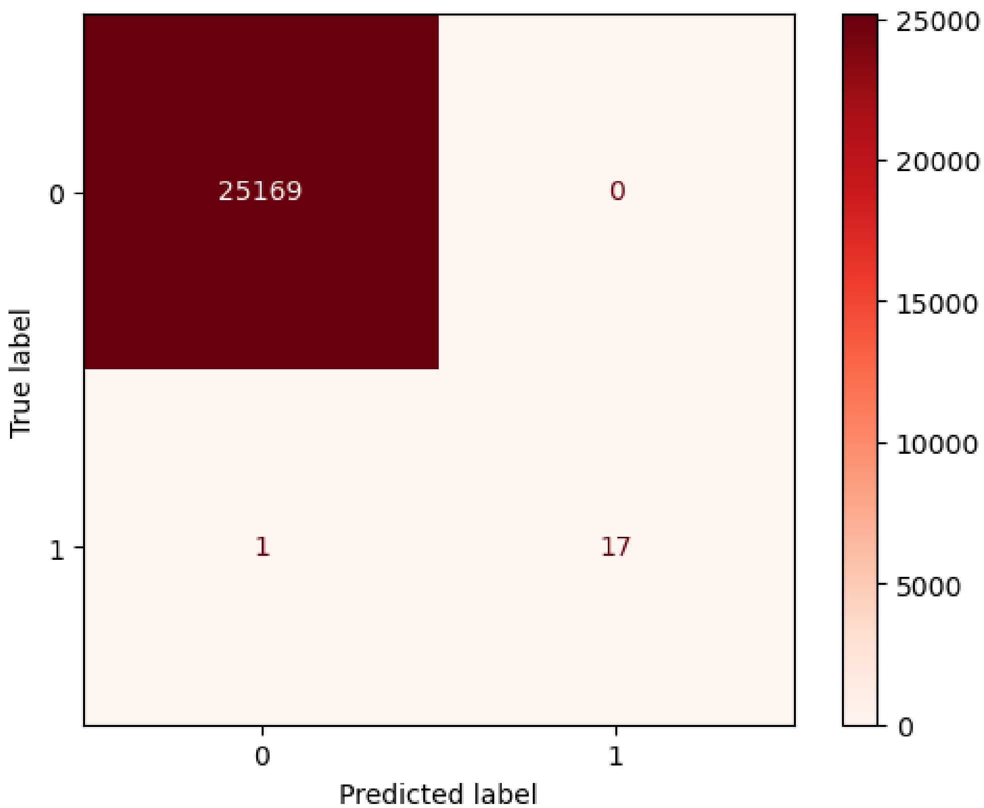


3.6 Voting Classifier

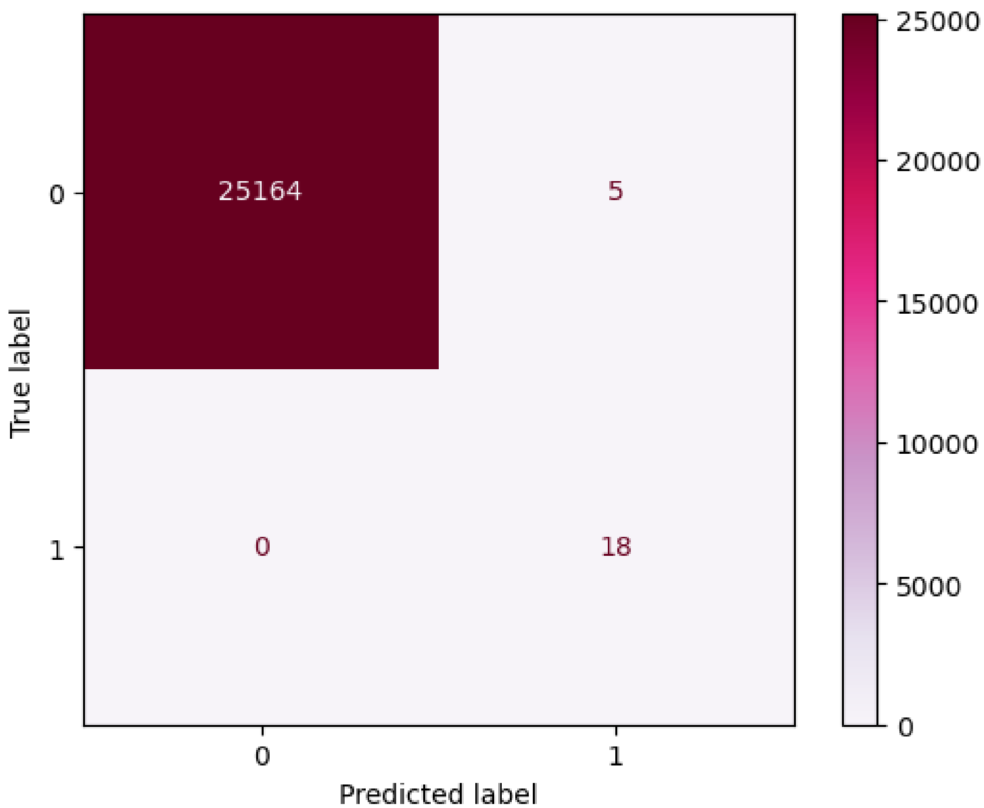
[96]:
```
# Voting Hard Model

from sklearn.ensemble import VotingClassifier


# group / ensemble of models
estimator = []
estimator.append(('LR', LogisticRegression(max_iter=1000,␣
 ↪class_weight='balanced', random_state=7)))
# estimator.append(('SVC', SVC(kernel='linear', class_weight='balanced',␣
 ↪probability=True, random_state=7)))
estimator.append(('RF', RandomForestClassifier(n_estimators=10, random_state=7)))
estimator.append(('DT', DecisionTreeClassifier(criterion="entropy",␣
 ↪random_state=7)))
estimator.append(('MLP', MLPClassifier(max_iter=1000,␣
 ↪hidden_layer_sizes=(12,6),activation="logistic",random_state = 7)))

# Voting Classifier with hard voting
```

```python
vot_hard = VotingClassifier(estimators = estimator, voting ='hard')
vot_hard.fit(train_resample_X, train_resample_y.values.ravel())

# using accuracy_score metric to predict accuracy
score = accuracy_score(test_y, vot_hard.predict(test_X))
print("Hard Voting Score % d" % score)

# Voting Classifier with soft voting
vot_soft = VotingClassifier(estimators = estimator, voting ='soft')
vot_soft.fit(train_resample_X, train_resample_y.values.ravel())

# using accuracy_score
score = accuracy_score(test_y, vot_soft.predict(test_X))
print("Soft Voting Score % d" % score)

# Plot Confusion Matrix - hard
print("Confusion matrix: ", confusion_matrix(test_y, vot_hard.predict(test_X)))
cm=confusion_matrix(test_y, vot_hard.predict(test_X))
plot_confusion_matrix(vot_hard, test_X, test_y, cmap=plt.cm.Reds)
plt.show()

# Plot Confusion Matrix - soft
print("Confusion matrix: ", confusion_matrix(test_y, vot_soft.predict(test_X)))
cm=confusion_matrix(test_y, vot_soft.predict(test_X))
plot_confusion_matrix(vot_soft, test_X, test_y, cmap=plt.cm.PuRd)
plt.show()
```

```
Hard Voting Score  0
Soft Voting Score  0
Confusion matrix:  [[25169     0]
 [    1    17]]
```




```
Confusion matrix:  [[25164     5]
 [    0    18]]
```



4 Evaluating and Concluding

4.1 Precision and Recall Comparison

[100]:
```
# Overall Comparison

models = [{'name': 'LR','label': 'Model 1: Logistic Regression',
           'classifier': LogisticRegression(max_iter=1000,␣
↪class_weight='balanced', random_state=7)},

          {'name': 'SVC', 'label': 'Model 2: Support Vector Machine',
           'classifier': SVC(kernel='linear', class_weight='balanced',␣
↪probability=True, random_state=7)},

          {'name': 'RF', 'label': 'Model 3: Random Forest',
           'classifier': RandomForestClassifier(n_estimators=10,␣
↪random_state=7)},

          {'name': 'DT','label': 'Model 4: Descision Tree',
```

```
          'classifier': DecisionTreeClassifier(criterion="entropy",␣
↪random_state=7)},

         {'name': 'MLP','label': 'Model 5: Neural Network',
          'classifier': MLPClassifier(max_iter=1000,␣
↪hidden_layer_sizes=(12,6),activation="logistic",random_state = 7)},

         {'name': 'VCH','label': 'Model 6: Voting Classifier - Hard',
          'classifier': VotingClassifier(estimators = estimator, voting␣
↪='hard')},

         {'name': 'VCS','label': 'Model 7: Voting Classifier - Soft',
          'classifier': VotingClassifier(estimators = estimator, voting␣
↪='soft')}]

models_AUC = [{'name': 'LR','label': 'Model 1: Logistic Regression',
          'classifier': LogisticRegression(max_iter=1000,␣
↪class_weight='balanced', random_state=7)},

         {'name': 'RF', 'label': 'Model 3: Random Forest',
          'classifier': RandomForestClassifier(n_estimators=10,␣
↪random_state=7)},

         {'name': 'DT','label': 'Model 4: Descision Tree',
          'classifier': DecisionTreeClassifier(criterion="entropy",␣
↪random_state=7)},

         {'name': 'MLP','label': 'Model 5: Neural Network',
          'classifier': MLPClassifier(max_iter=1000,␣
↪hidden_layer_sizes=(12,6),activation="logistic",random_state = 7)},

         {'name': 'VCS','label': 'Model 7: Voting Classifier - Soft',
          'classifier': VotingClassifier(estimators = estimator, voting␣
↪='soft')}]
```

[101]:

```
# Ruffle

from tqdm import tqdm
import time

for i in tqdm(range(10800)):
    time.sleep(0.1)

test_ori_X = test_X
test_ori_y = test_y
```

```
results = pd.DataFrame()
precision_result = []
recall_result = []
for m in models:
    m['classifier'].fit(train_resample_X, train_resample_y.values.ravel())
    pred_ori_y = m['classifier'].predict(test_ori_X)
    results.loc[m['label'], 'Accuracy'] = accuracy_score(test_ori_y, pred_ori_y)
    results.loc[m['label'], 'Precision_0'] = precision_score(test_ori_y,␣
 ↪pred_ori_y, pos_label = 0)
    results.loc[m['label'], 'Precision_1'] = precision_score(test_ori_y,␣
 ↪pred_ori_y, pos_label = 1)
    results.loc[m['label'], 'Recall_0'] = recall_score(test_ori_y, pred_ori_y,␣
 ↪pos_label = 0)
    results.loc[m['label'], 'Recall_1'] = recall_score(test_ori_y, pred_ori_y,␣
 ↪pos_label = 1)
```

[102]:
```
# Ruffle - AUC_pr score

from tqdm import tqdm
import time

for i in tqdm(range(10800)):
    time.sleep(0.1)

test_ori_X = test_X
test_ori_y = test_y

results_AUC = pd.DataFrame()
for m in models_AUC:
    m['classifier'].fit(train_resample_X, train_resample_y.values.ravel())
    probs = m['classifier'].predict_proba(test_ori_X)
    probs = probs[:,1]
    precision, recall, thresholds = precision_recall_curve(test_ori_y, probs)
    results_AUC.loc[m['label'], 'AUC_pr'] = auc(recall, precision)
```

[141]:
```
print(results_AUC)
```

```
                                    AUC_pr
Model 1: Logistic Regression      0.052511
Model 3: Random Forest            1.000000
Model 4: Descision Tree           1.000000
Model 5: Neural Network           0.161586
Model 7: Voting Classifier - Soft 0.996995
```

[106]:
```
# Ranking Based on Criteria AUC_pr > Recall_1 > Precision_1 > Accuracy
results.loc['Model 1: Logistic Regression','Ranking'] = 7
results.loc['Model 2: Support Vector Machine','Ranking'] = 6
```

```
results.loc['Model 3: Random Forest','Ranking'] = 2
results.loc['Model 4: Descision Tree','Ranking'] = 1
results.loc['Model 5: Neural Network','Ranking'] = 5
results.loc['Model 6: Voting Classifier - Hard','Ranking'] = 4
results.loc['Model 7: Voting Classifier - Soft','Ranking'] = 3
results['Ranking'] = results['Ranking'].astype(int)

print(results)
```

```
                                   Accuracy  Precision_0  Precision_1  \
Model 1: Logistic Regression       0.806210     0.999704     0.002455
Model 2: Support Vector Machine    0.798745     0.999751     0.002561
Model 3: Random Forest             1.000000     1.000000     1.000000
Model 4: Descision Tree            1.000000     1.000000     1.000000
Model 5: Neural Network            0.990630     0.999960     0.067460
Model 6: Voting Classifier - Hard  0.999960     0.999960     1.000000
Model 7: Voting Classifier - Soft  0.999801     1.000000     0.782609

                                   Recall_0  Recall_1  Ranking
Model 1: Logistic Regression       0.806309  0.666667        7
Model 2: Support Vector Machine    0.798800  0.722222        6
Model 3: Random Forest             1.000000  1.000000        2
Model 4: Descision Tree            1.000000  1.000000        1
Model 5: Neural Network            0.990663  0.944444        5
Model 6: Voting Classifier - Hard  1.000000  0.944444        4
Model 7: Voting Classifier - Soft  0.999801  1.000000        3
```

4.2 Conclusion and Recommendation

SMOTE upsampling based on each device with failure history is an effective way to improve the performance of all the machine learning models as well as GroupShuffleSplit method.

Learning from the history data of each device, the standard deviaion and percentage change are good indicators to represent the abnormal performance before each failure. Before failure, there is always unusual reading from some metrics. Having new features created as these indicators improves the performance of models significantly.

Recommendation: Based on the importance/criteria of this project to minimize false positives and false negatives, the recommended models are determined based on the ranking column as above. It shows the Decision Tree is best model with both Precision_1/Recall_1 with the highest scores as well as AUC_pr score. The 2nd and 3rd best models are the Random Forest and the Voting Classifier(Soft). I would recommend to use the Decision Tree as the final model with the best prediction performance designed for this project.