Predictive2

January 18, 2025

[1]:
```
!pip install xgboost -q
```

[2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim

from sklearn import decomposition
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor,␣
↪VotingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (
    accuracy_score,
    classification_report,
    confusion_matrix,
    ConfusionMatrixDisplay,
    mean_absolute_error,
    mean_squared_error,
    r2_score,
    roc_auc_score,
)
from sklearn.model_selection import (
    GridSearchCV,
    StratifiedKFold,
    cross_val_score,
    train_test_split,
)
from sklearn.neural_network import MLPClassifier
from sklearn.preprocessing import LabelEncoder, MinMaxScaler, StandardScaler
from sklearn.svm import SVC
from xgboost import XGBClassifier
from ipywidgets import interact, fixed
```

[3]:
```python
df=pd.read_csv('data.csv')
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 944 entries, 0 to 943
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   footfall     944 non-null    int64
 1   tempMode     944 non-null    int64
 2   AQ           944 non-null    int64
 3   USS          944 non-null    int64
 4   CS           944 non-null    int64
 5   VOC          944 non-null    int64
 6   RP           944 non-null    int64
 7   IP           944 non-null    int64
 8   Temperature  944 non-null    int64
 9   fail         944 non-null    int64
dtypes: int64(10)
memory usage: 73.9 KB
```

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

[5]:
```
          footfall    tempMode          AQ         USS          CS  \
count   944.000000  944.000000  944.000000  944.000000  944.000000
mean    306.381356    3.727754    4.325212    2.939619    5.394068
std    1082.606745    2.677235    1.438436    1.383725    1.269349
min       0.000000    0.000000    1.000000    1.000000    1.000000
25%       1.000000    1.000000    3.000000    2.000000    5.000000
50%      22.000000    3.000000    4.000000    3.000000    6.000000
75%     110.000000    7.000000    6.000000    4.000000    6.000000
max    7300.000000    7.000000    7.000000    7.000000    7.000000

              VOC          RP          IP  Temperature        fail
count  944.000000  944.000000  944.000000   944.000000  944.000000
mean     2.842161   47.043432    4.565678    16.331568    0.416314
std      2.273337   16.423130    1.599287     5.974781    0.493208
min      0.000000   19.000000    1.000000     1.000000    0.000000
25%      1.000000   34.000000    3.000000    14.000000    0.000000
50%      2.000000   44.000000    4.000000    17.000000    0.000000
75%      5.000000   58.000000    6.000000    21.000000    1.000000
max      6.000000   91.000000    7.000000    24.000000    1.000000
```

1 Missing values analysis

[6]:
```
df.isnull().sum()
```

[6]:
```
footfall       0
tempMode       0
AQ             0
USS            0
CS             0
VOC            0
RP             0
IP             0
Temperature    0
fail           0
dtype: int64
```

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

[7]:

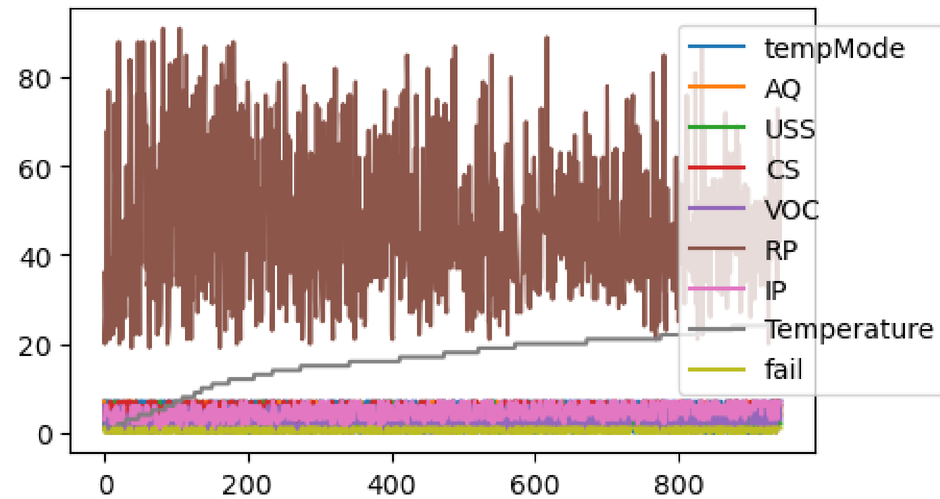
	footfall	tempMode	AQ	USS	CS	VOC	RP	IP	Temperature	fail
0	0	7	7	1	6	6	36	3	1	1
1	190	1	3	3	5	1	20	4	1	0
2	31	7	2	2	6	1	24	6	1	0
3	83	4	3	4	5	1	28	6	1	0
4	640	7	5	6	4	0	68	6	1	0

[8]:
```
df['fail'].value_counts()
```

[8]:
```
fail
0    551
1    393
Name: count, dtype: int64
```

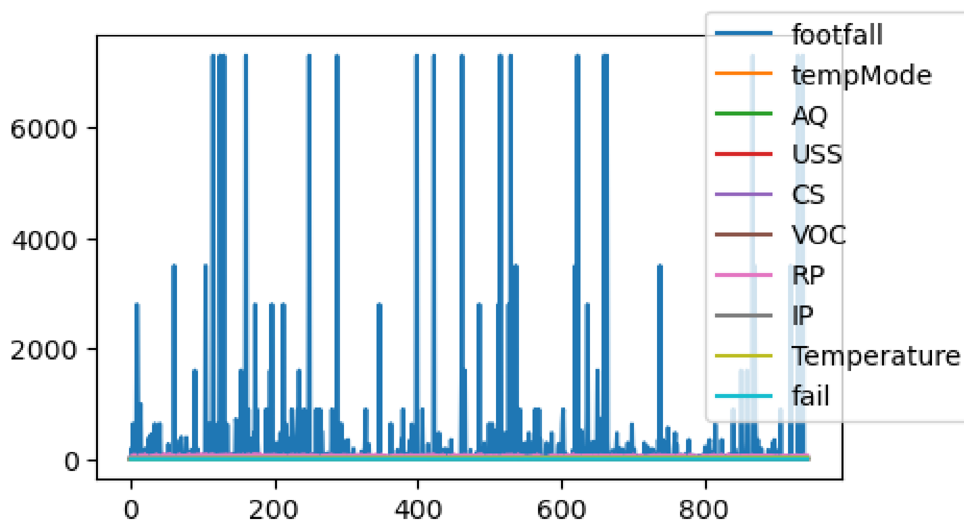
[9]:
```
plt.figure(figsize=(5,3))
for each in df.drop('footfall', axis=1):
    plt.plot(df[each], label=each)
plt.legend(loc="best",bbox_to_anchor=(0.8,0.1))
```

[9]:
```
<matplotlib.legend.Legend at 0x7f4045573c40>
```



[10]:
```
plt.figure(figsize=(5,3))
for each in df:
    plt.plot(df[each], label=each)
plt.legend(loc="best",bbox_to_anchor=(0.8,0.1))
```

[10]: <matplotlib.legend.Legend at 0x7f40376aa410>



2 Data distribution

[11]:
```
columns=df.columns

plt.figure(figsize=(17,15))
for i, col in enumerate(columns,1):
    plt.subplot(5,3, i)
    sns.histplot(df[col], kde=True)
    #plt.title(f'{col} distribution')
# plt.tight_layout()
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1498: FutureWarning:
is_categorical_dtype is deprecated and will be removed in a future version. Use
isinstance(dtype, CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning:
use_inf_as_na option is deprecated and will be removed in a future version.
Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1498: FutureWarning:
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```

```
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Convert inf values to NaN before operating instead.
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isinstance(dtype, CategoricalDtype) instead
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/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning:
use_inf_as_na option is deprecated and will be removed in a future version.
Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```
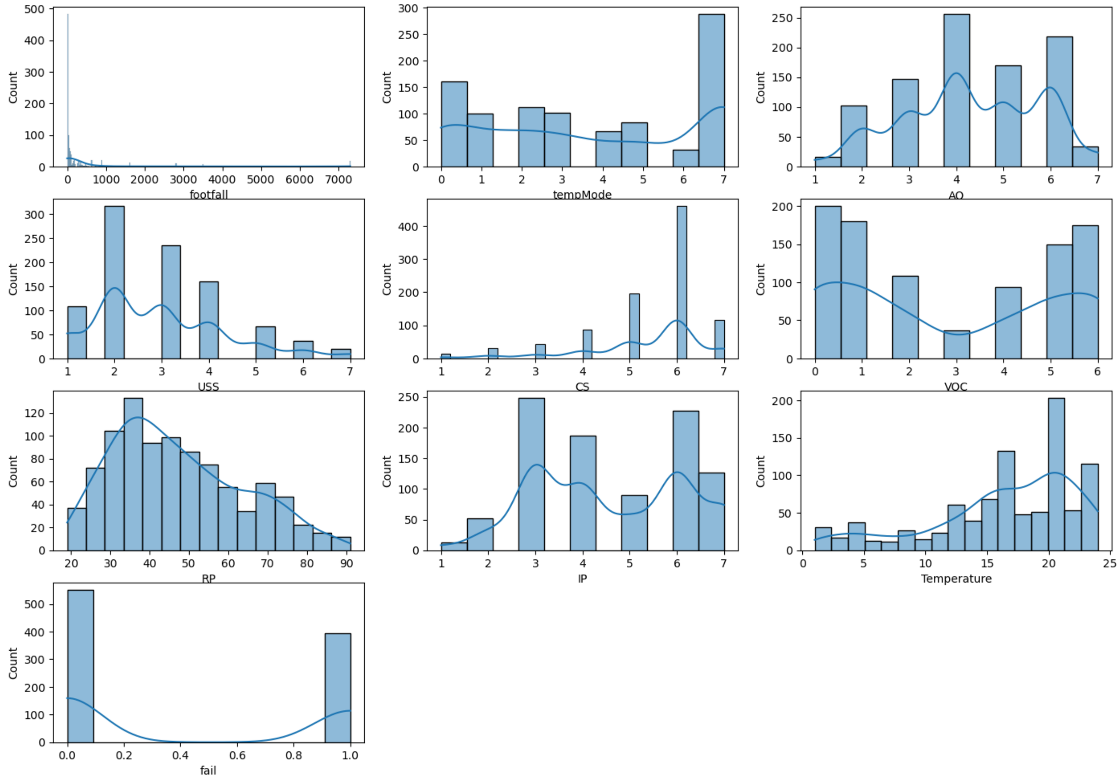
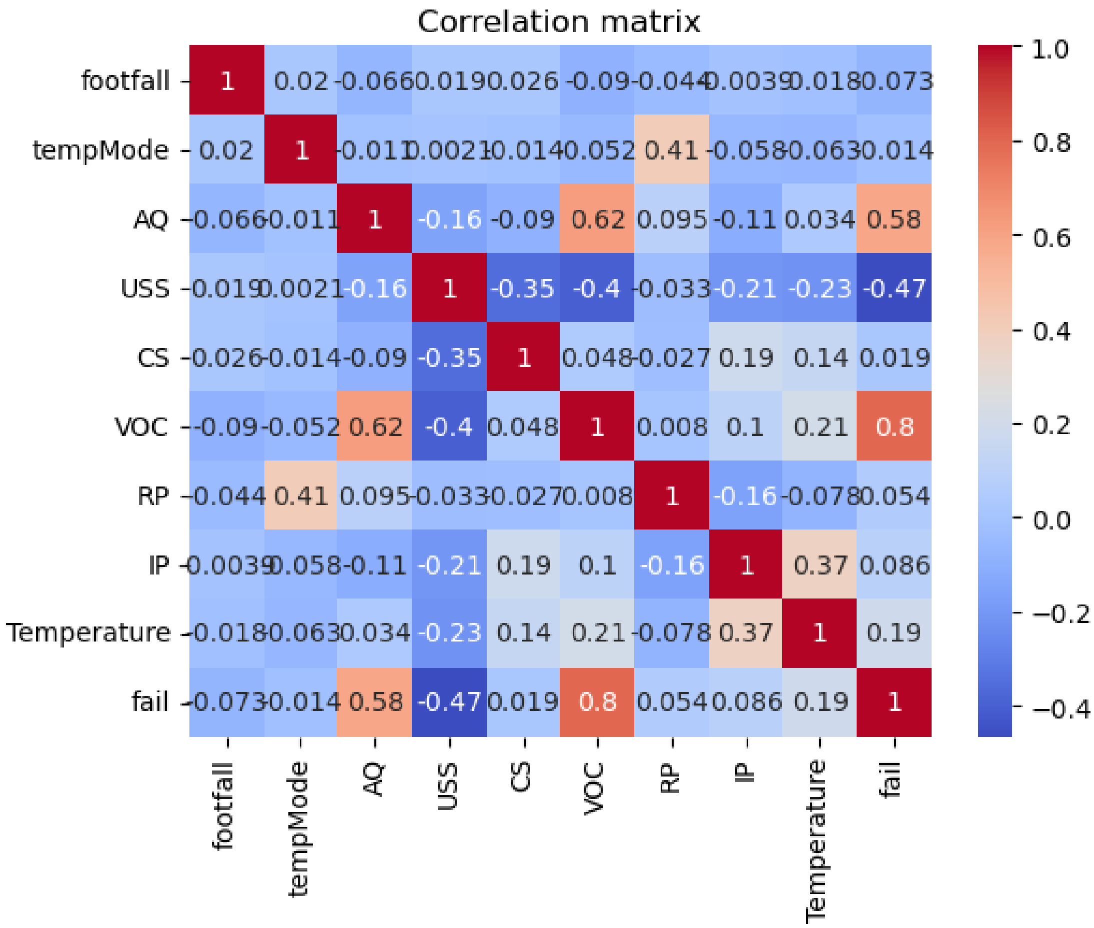



[12]:
```python
correlation=df.corr()
print(correlation)
sns.heatmap(correlation, cmap='coolwarm', annot=True)
plt.title('Correlation matrix')
```

```
             footfall  tempMode        AQ       USS        CS       VOC  \
footfall     1.000000  0.020457 -0.065816  0.019453  0.025638 -0.089590
tempMode     0.020457  1.000000 -0.010855  0.002142 -0.013956 -0.052369
AQ          -0.065816 -0.010855  1.000000 -0.156884 -0.090010  0.618570
USS          0.019453  0.002142 -0.156884  1.000000 -0.352915 -0.399477
CS           0.025638 -0.013956 -0.090010 -0.352915  1.000000  0.048037
VOC         -0.089590 -0.052369  0.618570 -0.399477  0.048037  1.000000
RP          -0.043720  0.408784  0.094656 -0.032549 -0.026968  0.008023
IP          -0.003869 -0.058109 -0.105868 -0.206416  0.185739  0.103628
Temperature -0.018009 -0.062568  0.034328 -0.225122  0.143972  0.208956
fail        -0.073066 -0.014462  0.583238 -0.466574  0.018855  0.797329

                   RP        IP  Temperature      fail
footfall    -0.043720 -0.003869    -0.018009 -0.073066
tempMode     0.408784 -0.058109    -0.062568 -0.014462
AQ           0.094656 -0.105868     0.034328  0.583238
USS         -0.032549 -0.206416    -0.225122 -0.466574
```

```
CS           -0.026968  0.185739     0.143972  0.018855
VOC           0.008023  0.103628     0.208956  0.797329
RP            1.000000 -0.158841    -0.078499  0.053668
IP           -0.158841  1.000000     0.372771  0.085624
Temperature -0.078499  0.372771     1.000000  0.190257
fail          0.053668  0.085624     0.190257  1.000000
```

[12]: Text(0.5, 1.0, 'Correlation matrix')



[13]:
```python
x=df.drop('fail',axis=1)
y=df['fail']
```

[14]:
```python
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.2,␣
↪random_state=42, stratify=y)#x
```

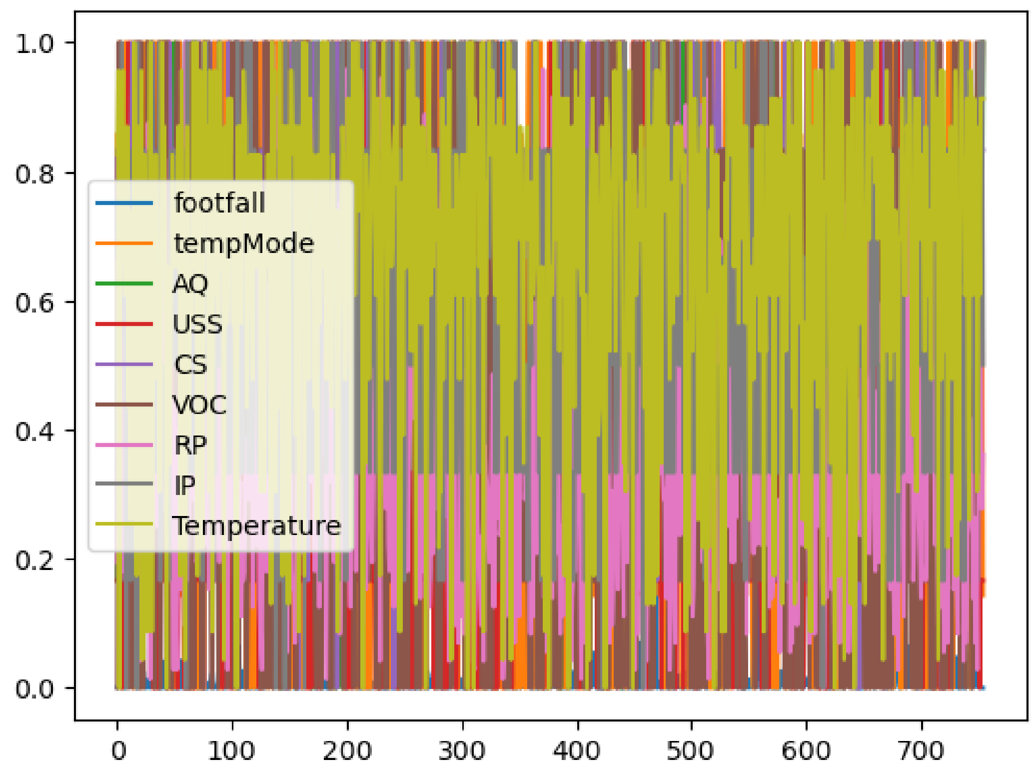
[15]:
```python
y_train.value_counts(), y_test.value_counts()
```

[15]: (fail
 0   441
 1   314
 Name: count, dtype: int64,
 fail
 0   110
 1   79
 Name: count, dtype: int64)

[16]:
```
mms= MinMaxScaler()

x_train_scaled=pd.DataFrame(mms.fit_transform(x_train),columns=x_train.columns)
x_test_scaled=pd.DataFrame(mms.transform(x_test),columns=x_test.columns)
```

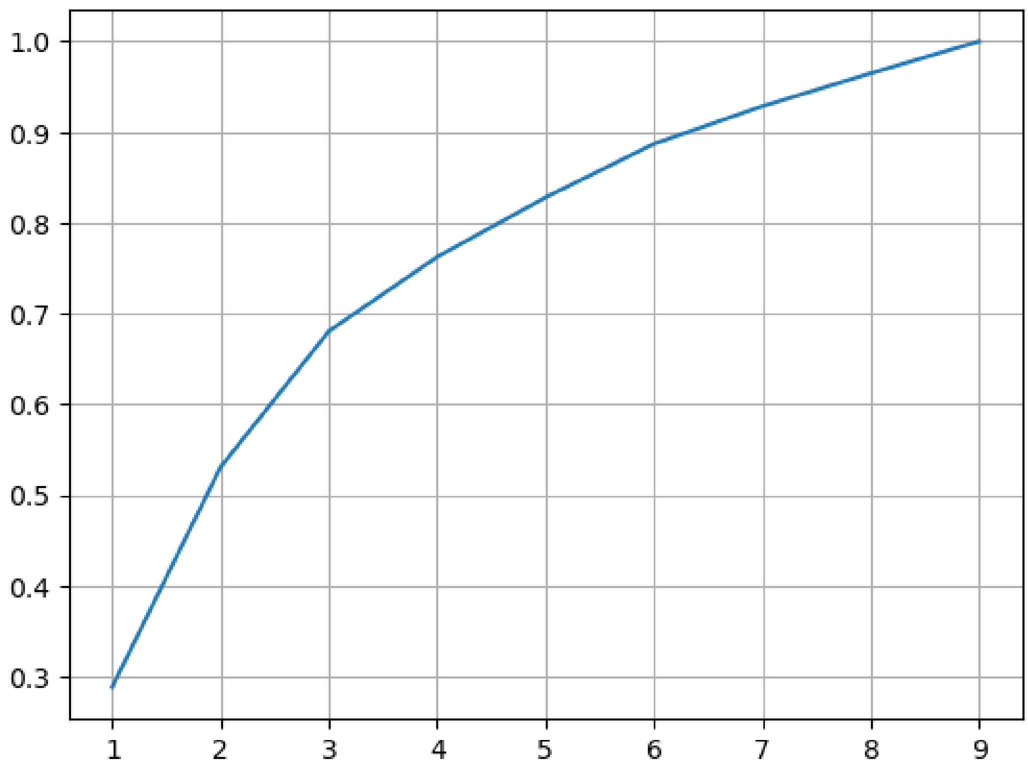
3 Visualization of scaled data

[17]:
```
for each in x_train_scaled:
    plt.plot(x_train_scaled[each], label=each)
plt.legend()
plt.show()
```



[18]:
```
pca= decomposition.PCA(n_components=x_train_scaled.columns.size)

pca.fit(x_train_scaled)

plt.plot(range(1,x_train_scaled.columns.size+1), np.cumsum(pca.
 ↪explained_variance_ratio_))
plt.grid()
################################
pca= decomposition.PCA(n_components=0.95) #preserving 95% of the information␣
 ↪#variance = quantity of information that each component can explain
df_pca = pca.fit_transform(x_train_scaled)

num_components = pca.n_components_
print(f"Number of components: {num_components}")
```

Number of components: 8



[19]:
```
pca=decomposition.PCA(n_components=8)

x_train_pca=pca.fit_transform(x_train_scaled)
x_test_pca=pca.transform(x_test_scaled)
#x_pca=pd.DataFrame(x_pca,columns=['pca1','pca2','pca3','pca4','pca5','pca6'])
```

```
x_train_pca, y
```

[19]:
```
(array([[ 0.48604853,  0.05599854, -0.46468965, …, -0.28091988,
          -0.13139069, -0.08680689],
         [-0.73707537, -0.03911392, -0.11037746, …,  0.12467169,
          -0.03964717, -0.0353786 ],
         [ 0.67228949,  0.42388588,  0.55048253, …,  0.43564987,
           0.17013245,  0.00951569],
         …,
         [-0.50239472,  0.25504131, -0.18664332, …,  0.23956027,
           0.06993415, -0.04647211],
         [-0.41720303,  0.35614706, -0.41010131, …, -0.05948752,
           0.05202576, -0.04788465],
         [-0.7943958 , -0.14277615,  0.14378027, …, -0.01871031,
           0.12538298, -0.0873974 ]]),
 0      1
 1      0
 2      0
 3      0
 4      0
       ..
 939    1
 940    1
 941    1
 942    1
 943    1
 Name: fail, Length: 944, dtype: int64)
```

[20]:
```
pd.DataFrame(x_train_pca)
```

[20]:
```
            0         1         2         3         4         5         6  \
0    0.486049  0.055999 -0.464690 -0.102039  0.030535 -0.280920 -0.131391
1   -0.737075 -0.039114 -0.110377  0.156834 -0.079276  0.124672 -0.039647
2    0.672289  0.423886  0.550483  0.179611  0.235864  0.435650  0.170132
3   -0.640874 -0.168995 -0.261251  0.016399  0.105728 -0.100890 -0.051414
4   -0.477463  0.306485 -0.396165 -0.021867  0.092109  0.116462 -0.065223
..        …         …         …         …         …         …         …
750  0.387150  0.120999  0.252188  0.293813 -0.289934  0.025618  0.076918
751 -0.601956  0.410020 -0.169092 -0.094829  0.225905  0.291173 -0.012706
752 -0.502395  0.255041 -0.186643  0.027458 -0.152145  0.239560  0.069934
753 -0.417203  0.356147 -0.410101  0.128916  0.176766 -0.059488  0.052026
754 -0.794396 -0.142776  0.143780 -0.041507 -0.231738 -0.018710  0.125383

            7
0   -0.086807
1   -0.035379
2    0.009516
```

```
3    0.140133
4   -0.071458
..        …
750 -0.056751
751 -0.076661
752 -0.046472
753 -0.047885
754 -0.087397

[755 rows x 8 columns]
```

4 Threshold for Accuracy

[21]:
```python
baseline_accuracy = y.value_counts().max()/len(y)
baseline_accuracy
```

[21]:
```
0.5836864406779662
```

5 Training - with outliers

[22]:
```python
# LogisticRegression


log_reg = LogisticRegression()
log_reg.fit(x_train_pca,y_train)
y_pred_log=log_reg.predict(x_test_pca)
print('Accuracy', accuracy_score(y_test,y_pred_log))
print(classification_report(y_test,y_pred_log))
```

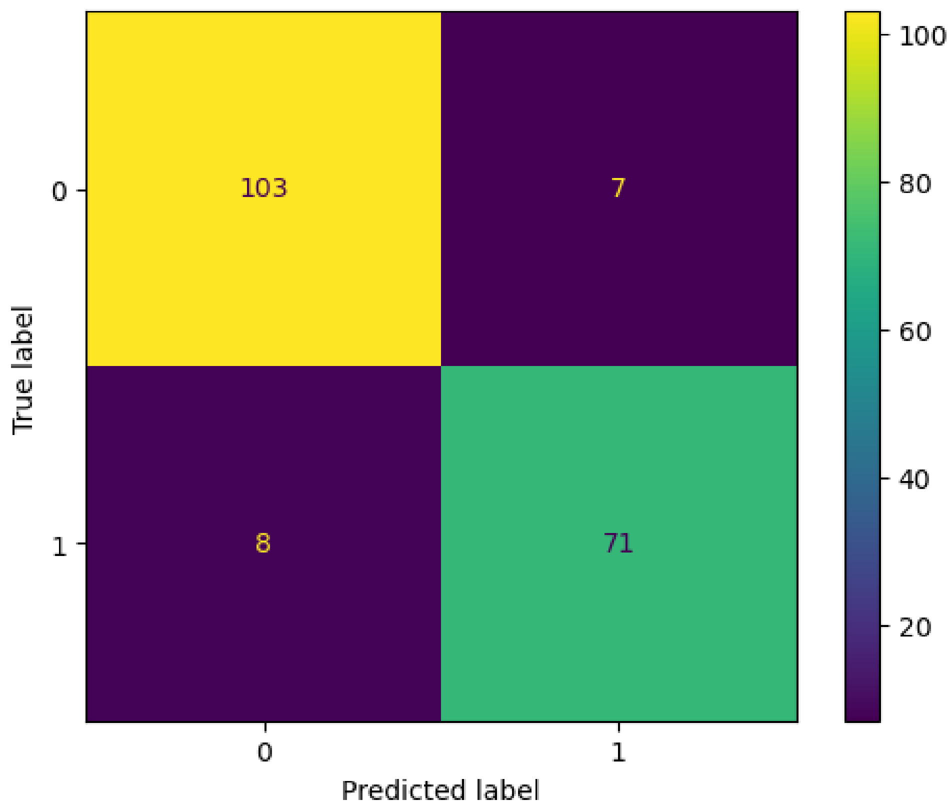
```
Accuracy 0.9153439153439153
              precision    recall  f1-score   support

           0       0.95      0.90      0.93       110
           1       0.87      0.94      0.90        79

    accuracy                           0.92       189
   macro avg       0.91      0.92      0.91       189
weighted avg       0.92      0.92      0.92       189
```

[23]:
```python
# RandomForestClassifier
rf_model=RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(x_train_pca, y_train)

y_pred_rf=rf_model.predict(x_test_pca)
```

```python
print('Accuracy', accuracy_score(y_test,y_pred_rf))
print(classification_report(y_test,y_pred_rf))
```

```
Accuracy 0.9206349206349206
              precision    recall  f1-score   support

           0       0.93      0.94      0.93       110
           1       0.91      0.90      0.90        79

    accuracy                           0.92       189
   macro avg       0.92      0.92      0.92       189
weighted avg       0.92      0.92      0.92       189
```

[24]:
```python
cm = confusion_matrix(y_test, y_pred_rf)
ConfusionMatrixDisplay(cm).plot()
plt.show()

auc_score = roc_auc_score(y_test, y_pred_rf)
print("ROC-AUC Score:", auc_score)
```



```
ROC-AUC Score: 0.9175489067894131
```

[25]:
```
import torch
X_train_np = x_train_pca
y_train_np = y_train.to_numpy().reshape(-1, 1)
X_test_np = x_test_pca
y_test_np = y_test.to_numpy().reshape(-1, 1)

X_train = torch.tensor(X_train_np, dtype=torch.float32)
y_train = torch.tensor(y_train_np, dtype=torch.float32)
X_test = torch.tensor(X_test_np, dtype=torch.float32)
y_test = torch.tensor(y_test_np, dtype=torch.float32)
```

[26]:
```
# multi layer perceptron
import torch.nn as nn
import torch.optim as optim


class MLP(nn.Module):
    def __init__(self):
        super(MLP, self).__init__()
        self.layers = nn.Sequential(
            nn.Linear(X_train.shape[1], 64),
            nn.ReLU(),
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Linear(32, 16),
            nn.ReLU(),
            nn.Linear(16, 1),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.layers(x)

model = MLP()
criterion = nn.BCELoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

#training
for epoch in range(100):
    optimizer.zero_grad()
    outputs = model(X_train)
    loss = criterion(outputs, y_train)
    loss.backward()
    optimizer.step()
```

[27]:
```python
model.eval()
with torch.no_grad():
    y_pred = model(X_test)
    y_pred_labels = (y_pred >= 0.5).int()


from sklearn.metrics import f1_score, precision_score, recall_score


f1 = f1_score(y_test, y_pred_labels)
precision = precision_score(y_test, y_pred_labels)
recall = recall_score(y_test, y_pred_labels)

print(f'F1 Score: {f1}')
print(f'Precision: {precision}')
print(f'Recall: {recall}')
```

```
F1 Score: 0.9135802469135801
Precision: 0.891566265060241
Recall: 0.9367088607594937
```

[28]:
```python
#Correlation with output variable
cor_target = abs(df.corr()["fail"])
#Selecting highly correlated features
relevant_features = cor_target[cor_target>0.3]
relevant_features
```

[28]:
```
AQ      0.583238
USS     0.466574
VOC     0.797329
fail    1.000000
Name: fail, dtype: float64
```

6 Test 2

7 Outlier analysis

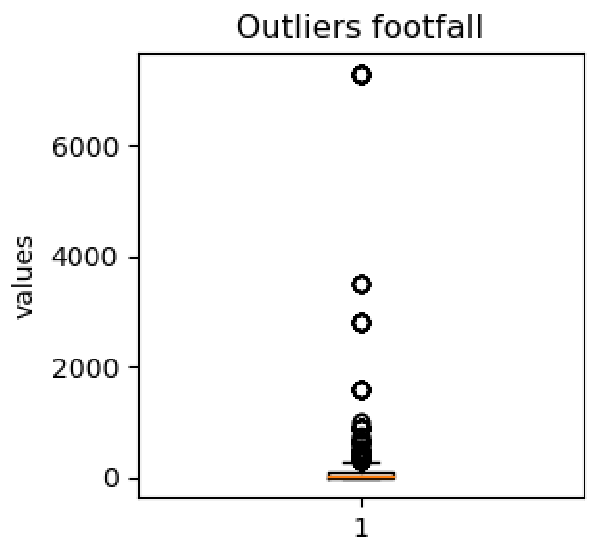
[29]:
```python
for each in df.columns:
    data = df[each]  # each column

    # Calculate IQR
    Q1 = data.quantile(0.25)
    Q3 = data.quantile(0.75)
    IQR = Q3 - Q1

    # Definir límites
```

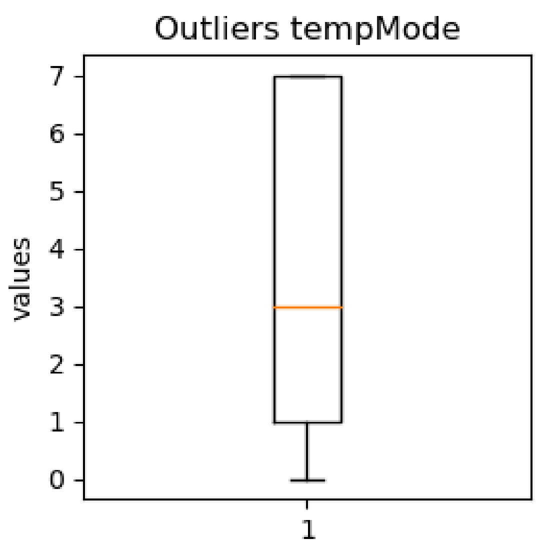
```
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Identify outliers
    outliers_index = data[(data < lower_bound) | (data > upper_bound)].index
    #to delete outliers
    # df_cleaned = df_cleaned[(df_cleaned[each] >= lower_bound) &
↪(df_cleaned[each] <= upper_bound)]

    print(f"Column: {each}")
    print(f"Number of outliers: {len(outliers_index)}")

    outliers_fail = df.loc[outliers_index, 'fail']
    print("'fail' outliers distribution:")
    print(outliers_fail.value_counts())
    print("-" * 40)
```

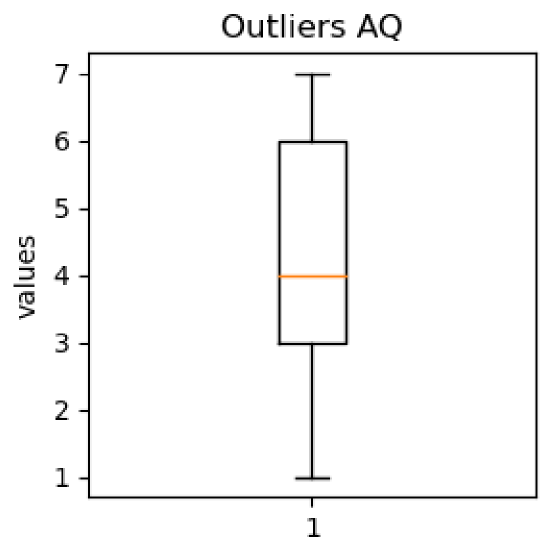
```
Column: footfall
Number of outliers: 154
'fail' outliers distribution:
fail
0    107
1     47
Name: count, dtype: int64
----------------------------------------
Column: tempMode
Number of outliers: 0
'fail' outliers distribution:
Series([], Name: count, dtype: int64)
----------------------------------------
Column: AQ
Number of outliers: 0
'fail' outliers distribution:
Series([], Name: count, dtype: int64)
----------------------------------------
Column: USS
Number of outliers: 0
'fail' outliers distribution:
Series([], Name: count, dtype: int64)
----------------------------------------
Column: CS
Number of outliers: 87
'fail' outliers distribution:
fail
0    71
1    16
Name: count, dtype: int64
```

```
---------------------------------------
Column: VOC
Number of outliers: 0
'fail' outliers distribution:
Series([], Name: count, dtype: int64)
---------------------------------------
Column: RP
Number of outliers: 0
'fail' outliers distribution:
Series([], Name: count, dtype: int64)
---------------------------------------
Column: IP
Number of outliers: 0
'fail' outliers distribution:
Series([], Name: count, dtype: int64)
---------------------------------------
Column: Temperature
Number of outliers: 48
'fail' outliers distribution:
fail
0    40
1     8
Name: count, dtype: int64
---------------------------------------
Column: fail
Number of outliers: 0
'fail' outliers distribution:
Series([], Name: count, dtype: int64)
---------------------------------------
```

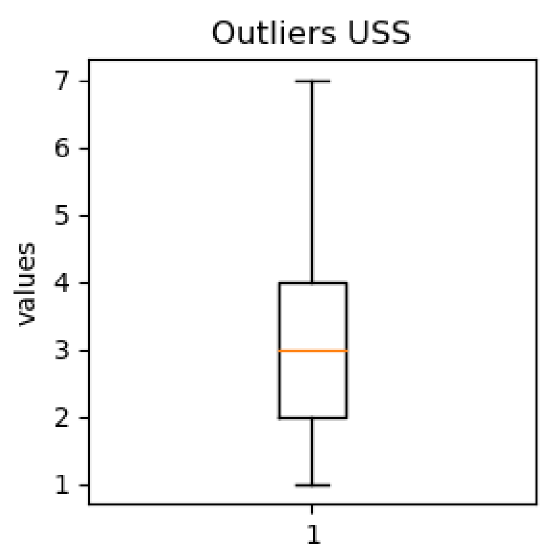
[30]:
```
for each in df.columns:
    plt.figure(figsize=(3,3))
    plt.boxplot(df[each])
    plt.title(f'Outliers {each}')
    plt.ylabel('values')
    plt.show()
```


Outliers footfall
values
6000
4000
2000
0
1

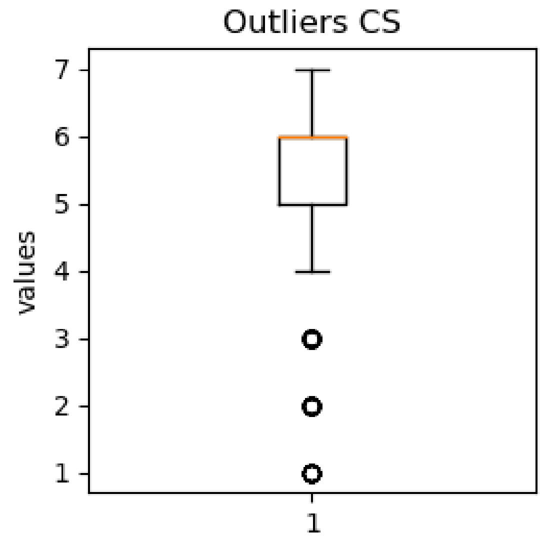

Outliers tempMode
values
7
6
5
4
3
2
1
0
1

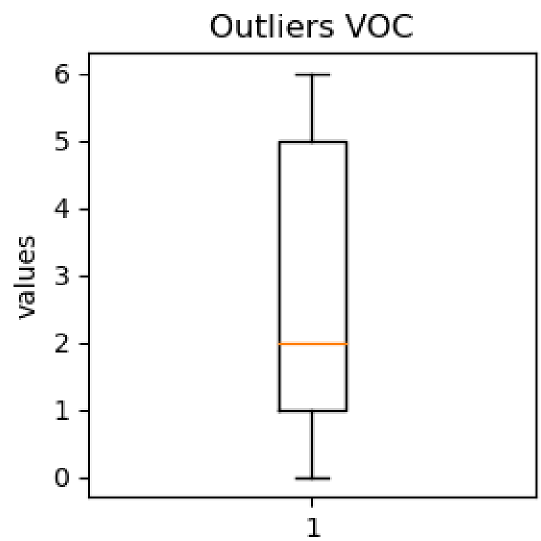


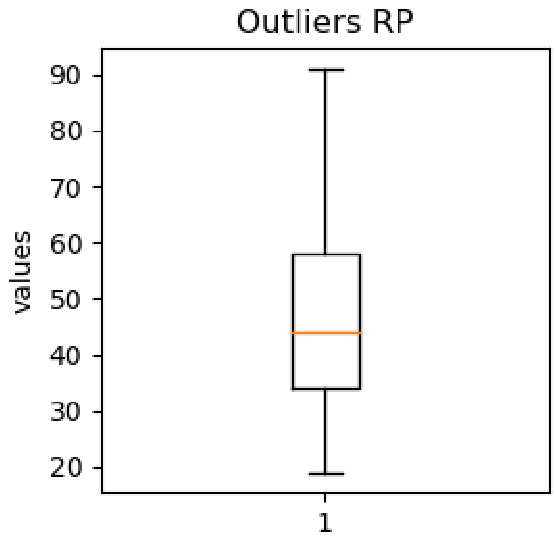
Outliers AQ
values
7
6
5
4
3
2
1
1

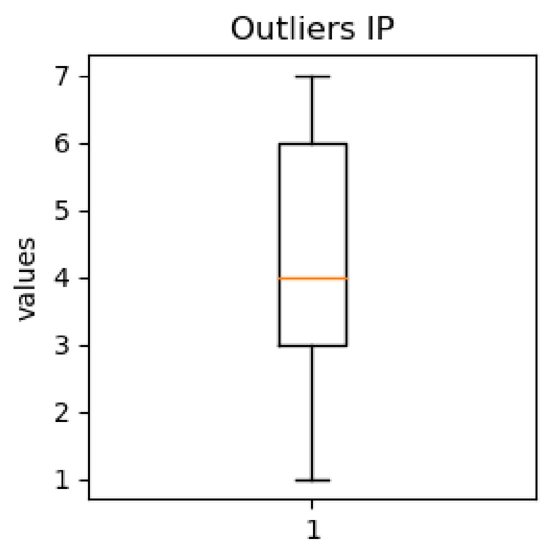


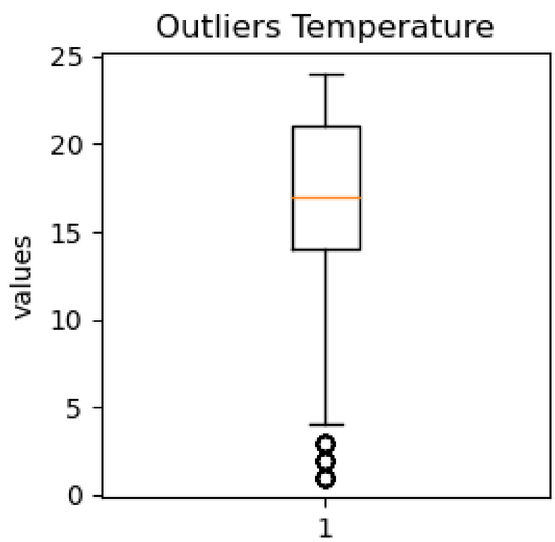
Outliers USS
values
7
6
5
4
3
2
1
1

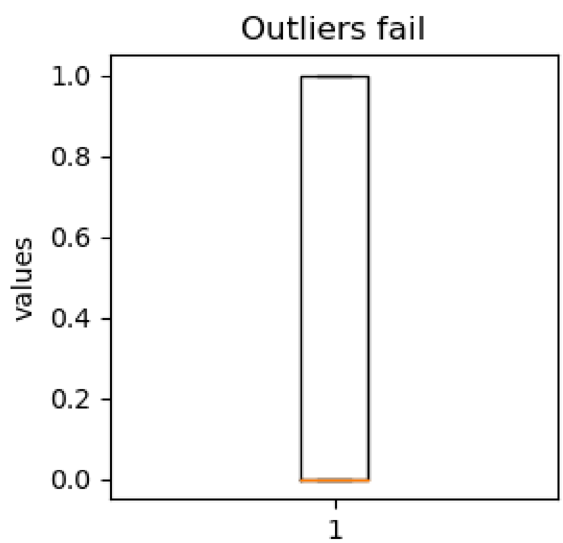

Outliers CS
values
7
6
5
4
3
2
1
1


Outliers VOC
values
6
5
4
3
2
1
0
1


Outliers RP
values
90
80
70
60
50
40
30
20
1


Outliers IP
values
7
6
5
4
3
2
1
1





[31]:
```
df['fail'].value_counts()
```

[31]:
```
fail
0    551
1    393
Name: count, dtype: int64
```

7.1 Delete outliers

[32]:
```
df_cleaned = df.copy()

columns_to_process = ['Temperature', 'CS']

for column in columns_to_process:
    data = df_cleaned[column]

    Q1 = data.quantile(0.25)
    Q3 = data.quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    df_cleaned = df_cleaned[(df_cleaned[column] >= lower_bound) &
↪(df_cleaned[column] <= upper_bound)]

for column in columns_to_process:
    data = df_cleaned[column]
    Q1 = data.quantile(0.25)
    Q3 = data.quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    outliers_index = data[(data < lower_bound) | (data > upper_bound)].index
    print(f"Column: {column}")
    print(f"Number of outliers remaining: {len(outliers_index)}")
```

```
Column: Temperature
Number of outliers remaining: 30
Column: CS
Number of outliers remaining: 0
```

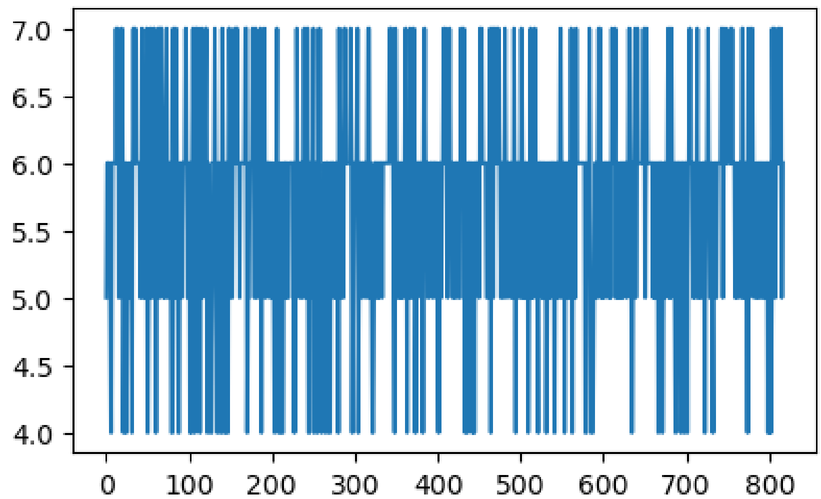
[33]:
```
print(f"Original DataFrame shape: {df.shape}")
print(f"Cleaned DataFrame shape: {df_cleaned.shape}")
```

```
Original DataFrame shape: (944, 10)
Cleaned DataFrame shape: (817, 10)
```

[34]:
```
df_cleaned.index=range(0,df_cleaned.shape[0])
```

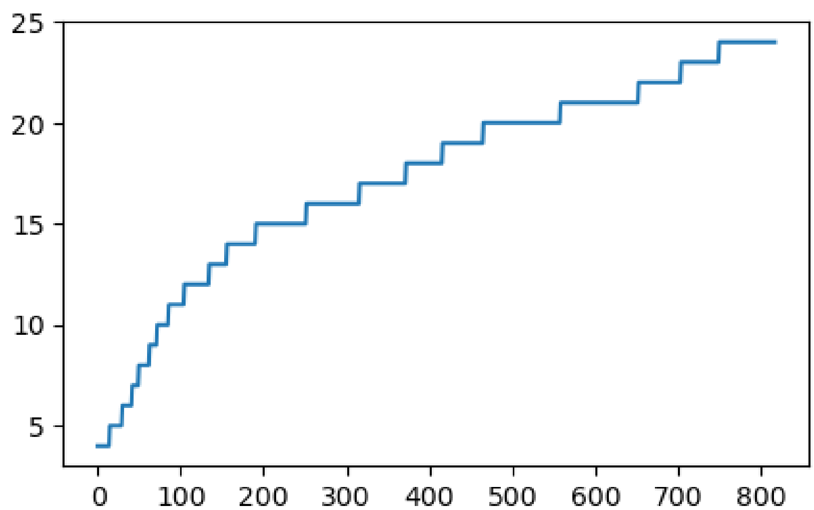
[35]:
```
plt.figure(figsize=(5,3))
plt.plot(df_cleaned['CS'])
```

[35]:
```
[<matplotlib.lines.Line2D at 0x7f400c46b9d0>]
```



[36]:
```
plt.figure(figsize=(5,3))
plt.plot(df_cleaned['Temperature'])
```

[36]: [<matplotlib.lines.Line2D at 0x7f400c4b9db0>]



8 Test without 'footfall' features and without outliers (Final test)

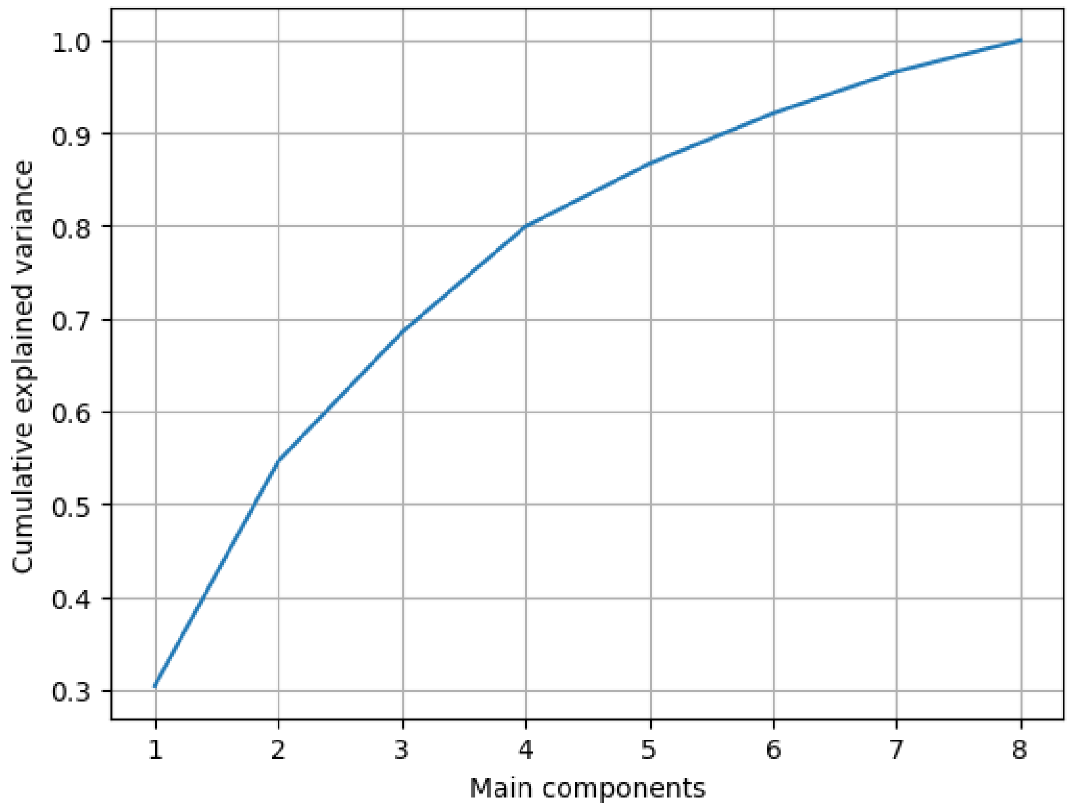
[37]:
```
x=df_cleaned.drop('fail',axis=1).drop('footfall',axis=1)
y=df_cleaned['fail']
```

[38]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
↪random_state=42, stratify=y)
```

[39]:
```
mms= MinMaxScaler((0,1))#StandardScaler()

x_train_scaled=pd.DataFrame(mms.fit_transform(x_train),columns=x_train.columns)
x_test_scaled=pd.DataFrame(mms.transform(x_test),columns=x_test.columns)
```

[40]:
```
pca= decomposition.PCA(n_components=x_train_scaled.columns.size)

pca.fit(x_train_scaled)

plt.plot(range(1,x_train_scaled.columns.size+1), np.cumsum(pca.
↪explained_variance_ratio_))
plt.grid()
plt.ylabel('Cumulative explained variance')
plt.xlabel('Main components')

#
pca= decomposition.PCA(n_components=0.95) #preserving 95% of the information␣
↪#variance = quantity of information that each component can explain
df_pca = pca.fit_transform(x_train_scaled)

num_components = pca.n_components_
print(f"Number of components: {num_components}")
```

```
Number of components: 7
```



[41]:
```
pca=decomposition.PCA(n_components=7)

x_train_pca=pca.fit_transform(x_train_scaled)
x_test_pca=pca.transform(x_test_scaled)
# x_pca=pd.DataFrame(x_pca,columns=['pca1','pca2','pca3','pca4','pca5','pca6'])
x_train_pca, y
x_train_pca_df=pd.DataFrame(x_train_pca)
```

[42]:
```
x_train_pca_df
```

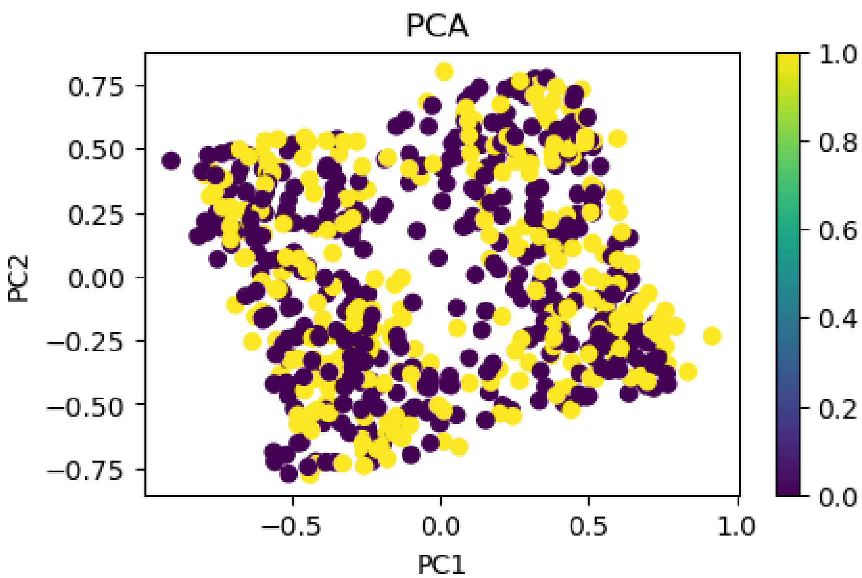
[42]:

	0	1	2	3	4	5	6
0	0.537744	-0.084918	-0.019218	-0.183941	-0.210332	0.167033	0.125222
1	-0.620786	-0.157385	-0.342914	0.040064	0.300420	-0.216781	0.071071
2	0.378876	0.683107	-0.179125	0.206882	0.156954	0.239662	-0.052792
3	0.210581	-0.503155	-0.148649	0.331629	-0.111456	0.235379	-0.068365
4	0.560739	-0.114943	0.227513	-0.229518	0.322598	-0.254968	-0.010368
..	…	…	…	…	…	…	…
648	0.712347	-0.207288	0.071820	0.158030	-0.029976	-0.009235	0.035325
649	-0.377107	0.181186	0.090721	-0.119260	0.045821	0.232109	0.072811
650	0.176518	0.602539	-0.059832	0.158517	0.330937	0.091321	0.093723
651	-0.734181	0.480270	0.591564	0.065837	0.228587	0.112374	0.297771

```
652 -0.457976 -0.392567  0.264795  0.342740 -0.194280 -0.218792 -0.281723

[653 rows x 7 columns]
```

8.1 To see the result of the PCA analysis

[43]:
```python
plt.figure(figsize=(5, 3))
#fig, ax = plt.subplots()
gr=plt.scatter(x_train_pca_df[0][:], x_train_pca_df[1][:], c=y[:653])
plt.colorbar(gr,orientation='vertical')
plt.title('PCA ')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.show()
```



The yellow dots represent the data with the target failure = 1

8.2 Cluster analysis

[44]:
```python
clusterer=KMeans(n_clusters=2)
```

[45]:
```python
clusterer.fit(x_train_pca_df)
y_cluster=clusterer.predict(x_train_pca_df)
```

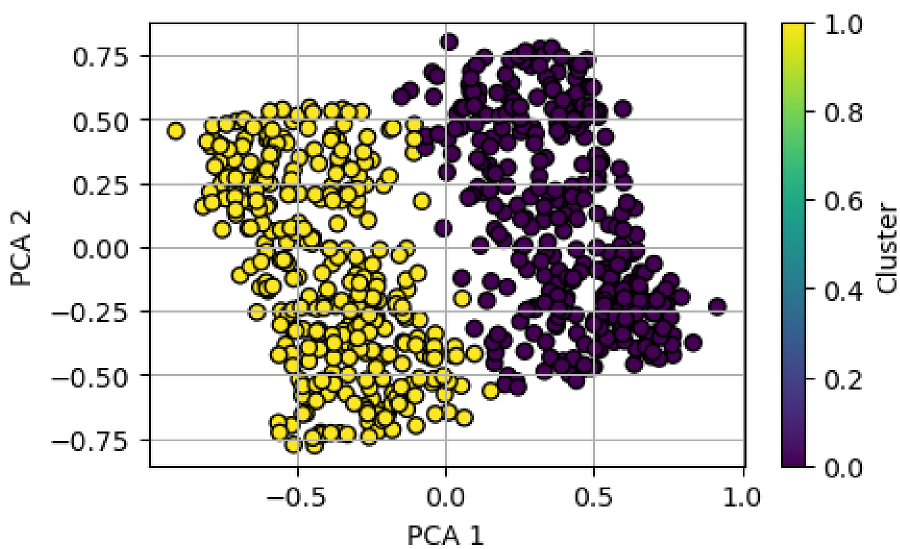
```
/opt/conda/lib/python3.10/site-packages/sklearn/cluster/_kmeans.py:1412:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
```

```
1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

[46]:
```python
y_cluster=pd.DataFrame(y_cluster)
y_cluster.value_counts()
```

[46]:
```
1    329
0    324
Name: count, dtype: int64
```

[47]:
```python

plt.figure(figsize=(5, 3))
plt.scatter(
    x_train_pca_df[0][:],
    x_train_pca_df[1][:],
    c=y_cluster[:],
    cmap='viridis',
    edgecolor='k'
)

plt.xlabel('PCA 1')
plt.ylabel('PCA 2')
plt.colorbar(label='Cluster')
plt.grid()
plt.show()
```



The cluster analusys show two different clusters

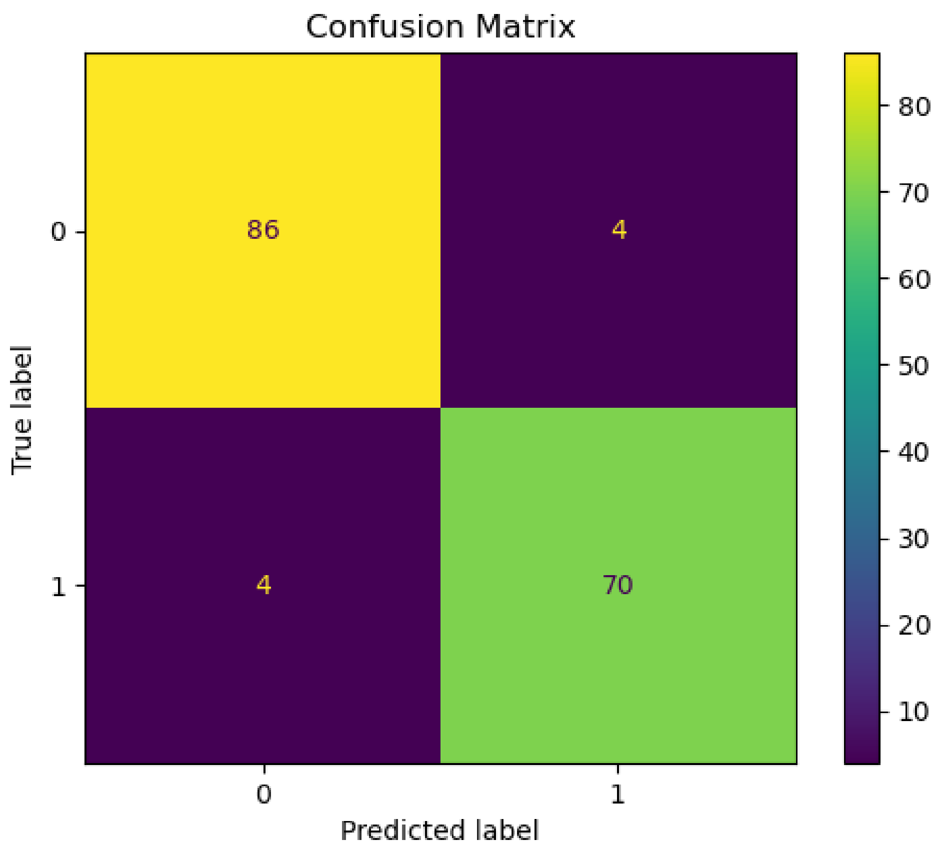
9 Model training

9.1 LogisticRegression

[48]:
```
log_reg = LogisticRegression()
log_reg.fit(x_train_pca,y_train)
y_pred_log=log_reg.predict(x_test_pca)
print('Accuracy', accuracy_score(y_test,y_pred_log))
print(classification_report(y_test,y_pred_log))
```

```
Accuracy 0.9512195121951219
              precision    recall  f1-score   support

           0       0.96      0.96      0.96        90
           1       0.95      0.95      0.95        74

    accuracy                           0.95       164
   macro avg       0.95      0.95      0.95       164
weighted avg       0.95      0.95      0.95       164
```

[49]:
```
cm = confusion_matrix(y_test, y_pred_log)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=[0, 1])
disp.plot()
plt.title('Confusion Matrix')
plt.show()
```



10 Cross validation to ensure that the model can generalize

[50]:
```
# Loading and preparing data
x1 = df_cleaned.drop(['fail', 'footfall'], axis=1)
y1 = df_cleaned['fail'].values  # convert to numpy array

# Scaling the data
mms = MinMaxScaler((0, 1))
x_scaled1 = pd.DataFrame(mms.fit_transform(x1), columns=x1.columns)

# Perform PCA
pca = PCA(n_components=7)  # Adjust the number of components as needed
x_pca1 = pca.fit_transform(x_scaled1)

# Base model: logistic regression
log_reg = LogisticRegression()

# Perform cross-validation (K-fold)
```

```python
kf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)  # 5-fold␣
 ↪cross-validation

# Use cross_val_score to get the cross-validation scores
cv_scores = cross_val_score(log_reg, x_pca1, y1, cv=kf, scoring='accuracy')

print(f'Accuracy por fold: {cv_scores}')
print(f'Mean Accuracy: {cv_scores.mean()}')
print(f'Standard Deviation of Accuracy: {cv_scores.std()}')

# Optional: If you want the details of each fold (more information than just␣
 ↪the score)
for train_idx, val_idx in kf.split(x_pca1, y1):
    x_train1, x_val1 = x_pca1[train_idx], x_pca1[val_idx]
    y_train1, y_val1 = y1[train_idx], y1[val_idx]  # numpy array, no Series

    # Training
    log_reg.fit(x_train1, y_train1)
    y_pred1 = log_reg.predict(x_val1)


    print("Classification Report for Fold")
    print(classification_report(y_val1, y_pred1))
```

```
Accuracy por fold: [0.93902439 0.90243902 0.91411043 0.90797546 0.93251534]
Mean Accuracy: 0.9192129283256023
Standard Deviation of Accuracy: 0.014164237718877969
Classification Report for Fold
              precision    recall  f1-score   support

           0       0.93      0.97      0.95        90
           1       0.96      0.91      0.93        74

    accuracy                           0.94       164
   macro avg       0.94      0.94      0.94       164
weighted avg       0.94      0.94      0.94       164

Classification Report for Fold
              precision    recall  f1-score   support

           0       0.92      0.90      0.91        90
           1       0.88      0.91      0.89        74

    accuracy                           0.90       164
   macro avg       0.90      0.90      0.90       164
weighted avg       0.90      0.90      0.90       164
```

```
Classification Report for Fold
              precision    recall  f1-score   support

           0       0.93      0.91      0.92        89
           1       0.89      0.92      0.91        74

    accuracy                           0.91       163
   macro avg       0.91      0.91      0.91       163
weighted avg       0.91      0.91      0.91       163

Classification Report for Fold
              precision    recall  f1-score   support

           0       0.96      0.87      0.91        89
           1       0.86      0.96      0.90        74

    accuracy                           0.91       163
   macro avg       0.91      0.91      0.91       163
weighted avg       0.91      0.91      0.91       163

Classification Report for Fold
              precision    recall  f1-score   support

           0       0.95      0.92      0.94        89
           1       0.91      0.95      0.93        74

    accuracy                           0.93       163
   macro avg       0.93      0.93      0.93       163
weighted avg       0.93      0.93      0.93       163
```

11 SVM

[51]:
```python
# SVM
svm_model = SVC(kernel='rbf', random_state=42)
svm_model.fit(x_train_pca, y_train)

# Predictions and evaluation
y_pred_svm = svm_model.predict(x_test_pca)
print("SVM Accuracy:", accuracy_score(y_test, y_pred_svm))
#print(classification_report(y_test, y_pred_svm))
```

```
SVM Accuracy: 0.9451219512195121
```

12 Random Forest

[52]:
```
rf_model=RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(x_train_pca, y_train)

y_pred_rf=rf_model.predict(x_test_pca)
print('Random Forest Accuracy:', accuracy_score(y_test,y_pred_rf))
#print(classification_report(y_test,y_pred_rf))
```

```
Random Forest Accuracy: 0.926829268292683
```

13 Multi-Layer Perceptron (MLP)

[53]:
```
# MLP
mlp_model = MLPClassifier(hidden_layer_sizes=(100,), max_iter=500,
 ↪random_state=42)
mlp_model.fit(x_train_pca, y_train)

y_pred_mlp = mlp_model.predict(x_test_pca)
print("MLP Accuracy:", accuracy_score(y_test, y_pred_mlp))
print(classification_report(y_test, y_pred_mlp))
```

```
MLP Accuracy: 0.9512195121951219
              precision    recall  f1-score   support

           0       0.96      0.96      0.96        90
           1       0.95      0.95      0.95        74

    accuracy                           0.95       164
   macro avg       0.95      0.95      0.95       164
weighted avg       0.95      0.95      0.95       164
```

14 Deep Neural Network (DNN)

[54]:
```
# Converting data to tensors
X_train_tensor = torch.tensor(x_train_pca, dtype=torch.float32)
y_train_tensor = torch.tensor(y_train.to_numpy().reshape(-1, 1), dtype=torch.
 ↪float32)
X_test_tensor = torch.tensor(x_test_pca, dtype=torch.float32)
y_test_tensor = torch.tensor(y_test.to_numpy().reshape(-1, 1), dtype=torch.
 ↪float32)

# Definition of DNN model
class DNN(nn.Module):
    def __init__(self, input_size):
```

```
        super(DNN, self).__init__()
        self.layers = nn.Sequential(
            nn.Linear(input_size, 128),
            nn.ReLU(),
            nn.Linear(128, 64),
            nn.ReLU(),
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Linear(32, 1),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.layers(x)
```

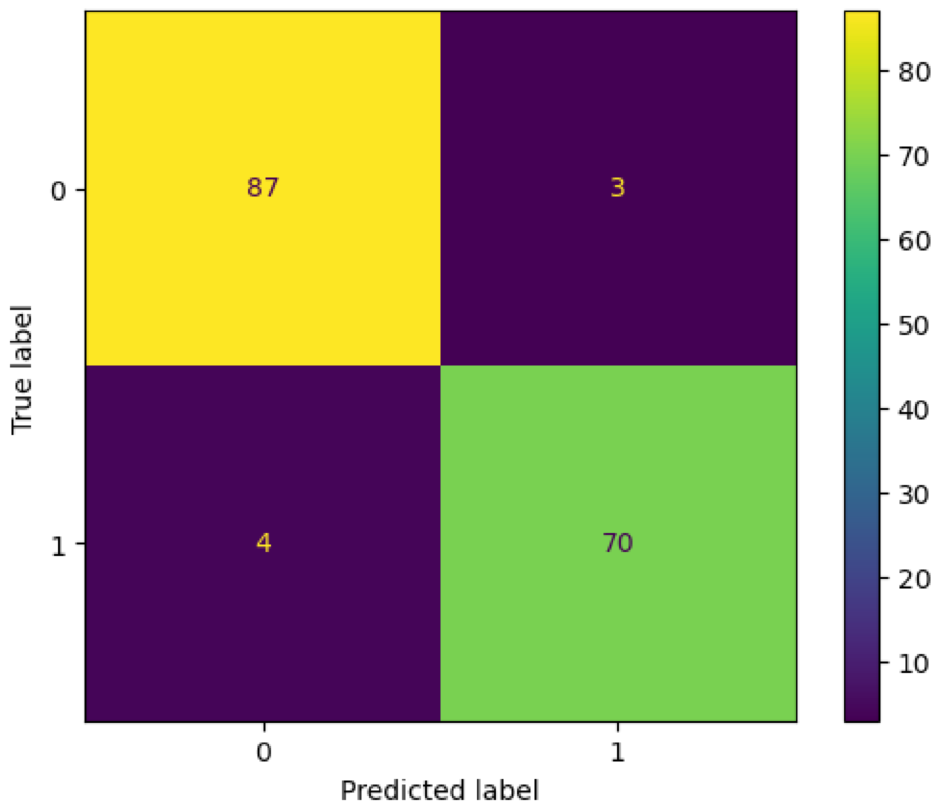
[55]:

```
# Model initialization
input_size = X_train_tensor.shape[1]
model = DNN(input_size)

# Definition of the loss function and the optimizer
criterion = nn.BCELoss()  # Binary Cross-Entropy Loss for binary problems
optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training
epochs = 100
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    y_pred = model(X_train_tensor)
    loss = criterion(y_pred, y_train_tensor)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 10 == 0:  # Print the loss every 10 epochs
        print(f"Epoch [{epoch + 1}/{epochs}], Loss: {loss.item():.4f}")

# Model evaluation
model.eval()
with torch.no_grad():
    y_pred_probs = model(X_test_tensor)
    y_pred_labels = (y_pred_probs >= 0.5).int()


accuracy = accuracy_score(y_test, y_pred_labels)
print("Accuracy: %.2f" % accuracy)
```

```
Epoch [10/100], Loss: 0.6587
```

```
Epoch [20/100], Loss: 0.5973
Epoch [30/100], Loss: 0.4981
Epoch [40/100], Loss: 0.3851
Epoch [50/100], Loss: 0.2897
Epoch [60/100], Loss: 0.2375
Epoch [70/100], Loss: 0.2183
Epoch [80/100], Loss: 0.2090
Epoch [90/100], Loss: 0.2033
Epoch [100/100], Loss: 0.1993
Accuracy: 0.96
```

[56]:
```python
cm = confusion_matrix(y_test, y_pred_labels)
ConfusionMatrixDisplay(cm).plot()
plt.show()

auc_score = roc_auc_score(y_test, y_pred_labels)
print(f"ROC-AUC Score: {auc_score:.2f}")
```




```
ROC-AUC Score: 0.96
```

15 Implementation

[57]:
```
# Save the weights of the trained model
torch.save(model.state_dict(), 'dnn_model.pth')
# To load the model after
model = DNN(input_size)
model.load_state_dict(torch.load('dnn_model.pth'))
model.eval()
```

[57]:
```
DNN(
  (layers): Sequential(
    (0): Linear(in_features=7, out_features=128, bias=True)
    (1): ReLU()
    (2): Linear(in_features=128, out_features=64, bias=True)
    (3): ReLU()
    (4): Linear(in_features=64, out_features=32, bias=True)
    (5): ReLU()
    (6): Linear(in_features=32, out_features=1, bias=True)
    (7): Sigmoid()
  )
)
```

[58]:
```
scaler = MinMaxScaler((0, 1))
scaler.fit(x_train)  # Use the adjusted values from training
pca = PCA(n_components=7)
pca.fit(x_train_scaled)


def preprocess_data(new_data):
    new_data_scaled = scaler.transform(new_data)
    new_data_pca = pca.transform(new_data_scaled)
    return torch.tensor(new_data_pca, dtype=torch.float32)
```

[59]:
```
def realtime_prediction(model, new_data):
    processed_data = preprocess_data(new_data)
    with torch.no_grad():
        prediction = model(processed_data)
        return (prediction >= 0.5).int().numpy()
```

[60]:
```
x_test[0:2], y_test[1:2]
```

[60]:
```
(     tempMode  AQ  USS  CS  VOC  RP  IP  Temperature
 158         0   6    4   7    3  68   6           14
 763         7   4    2   6    4  33   5           24,
 763    1
 Name: fail, dtype: int64)
```

[61]:
```
new_data = np.array([[0,6,4,7,3,68,6,14]])  # Replace with real data
#new_data = np.array(x_test[1:2])
predicted_label = realtime_prediction(model, new_data)
print("Prediction:", predicted_label)
```

```
Prediction: [[0]]

/opt/conda/lib/python3.10/site-packages/sklearn/base.py:464: UserWarning: X does
not have valid feature names, but MinMaxScaler was fitted with feature names
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/sklearn/base.py:464: UserWarning: X does
not have valid feature names, but PCA was fitted with feature names
  warnings.warn(
```

[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

16 Additional experiments

17 Trying to predict future failure

17.1 Trying to detect the failure 5 mearurements prior the real failure

[62]:
```
df_cleaned.index=range(0,df_cleaned.shape[0])
df_cleaned['future_fail'] = df_cleaned['fail'].shift(-1)
df_cleaned['future_fail'].fillna(0, inplace=True)
```

[63]:
```
x=df_cleaned.drop('fail',axis=1).drop('footfall',axis=1).
 ↪drop('future_fail',axis=1)
y=df_cleaned['future_fail']
```

[64]:
```
print(df_cleaned['future_fail'].value_counts(normalize=True))
```

```
future_fail
0.0    0.547124
1.0    0.452876
Name: proportion, dtype: float64
```

[65]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
 ↪random_state=42, stratify=y)
```

[66]:
```
mms= MinMaxScaler((0,1))#StandardScaler()

x_train_scaled=pd.DataFrame(mms.fit_transform(x_train),columns=x_train.columns)
x_test_scaled=pd.DataFrame(mms.transform(x_test),columns=x_test.columns)
```

[67]:
```
pca=decomposition.PCA(n_components=7)

x_train_pca=pca.fit_transform(x_train_scaled)
x_test_pca=pca.transform(x_test_scaled)
# x_pca=pd.DataFrame(x_pca,columns=['pca1','pca2','pca3','pca4','pca5','pca6'])
x_train_pca, y
x_train_pca_df=pd.DataFrame(x_train_pca)
```

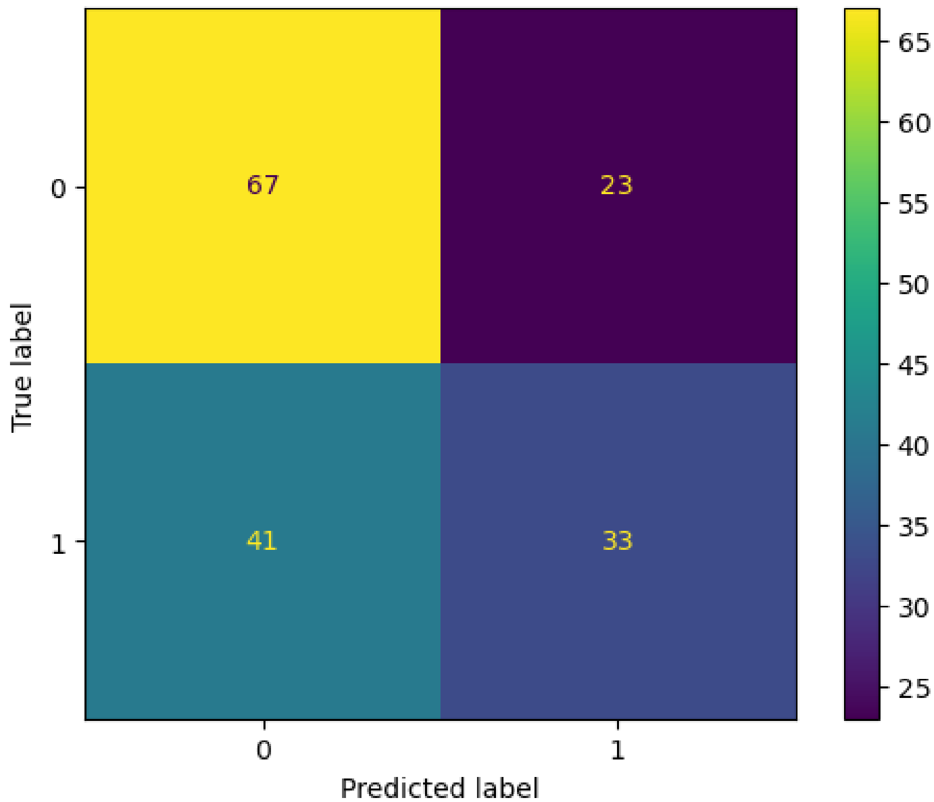
[68]:
```
log_reg = LogisticRegression()
log_reg.fit(x_train_scaled,y_train)
y_pred_log=log_reg.predict(x_test_scaled)
print('Accuracy', accuracy_score(y_test,y_pred_log))
print(classification_report(y_test,y_pred_log))
```

```
Accuracy 0.5426829268292683
              precision    recall  f1-score   support

         0.0       0.56      0.77      0.65        90
         1.0       0.49      0.27      0.35        74

    accuracy                           0.54       164
   macro avg       0.52      0.52      0.50       164
weighted avg       0.53      0.54      0.51       164
```

[69]:
```
rf_model=RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(x_train_pca, y_train)

y_pred_rf=rf_model.predict(x_test_pca)
print('Accuracy', accuracy_score(y_test,y_pred_rf))
print(classification_report(y_test,y_pred_rf))


cm = confusion_matrix(y_test, y_pred_rf)
ConfusionMatrixDisplay(cm).plot()
plt.show()

auc_score = roc_auc_score(y_test, y_pred_rf)
print("ROC-AUC Score:", auc_score)
```

```
Accuracy 0.6097560975609756
              precision    recall  f1-score   support
```

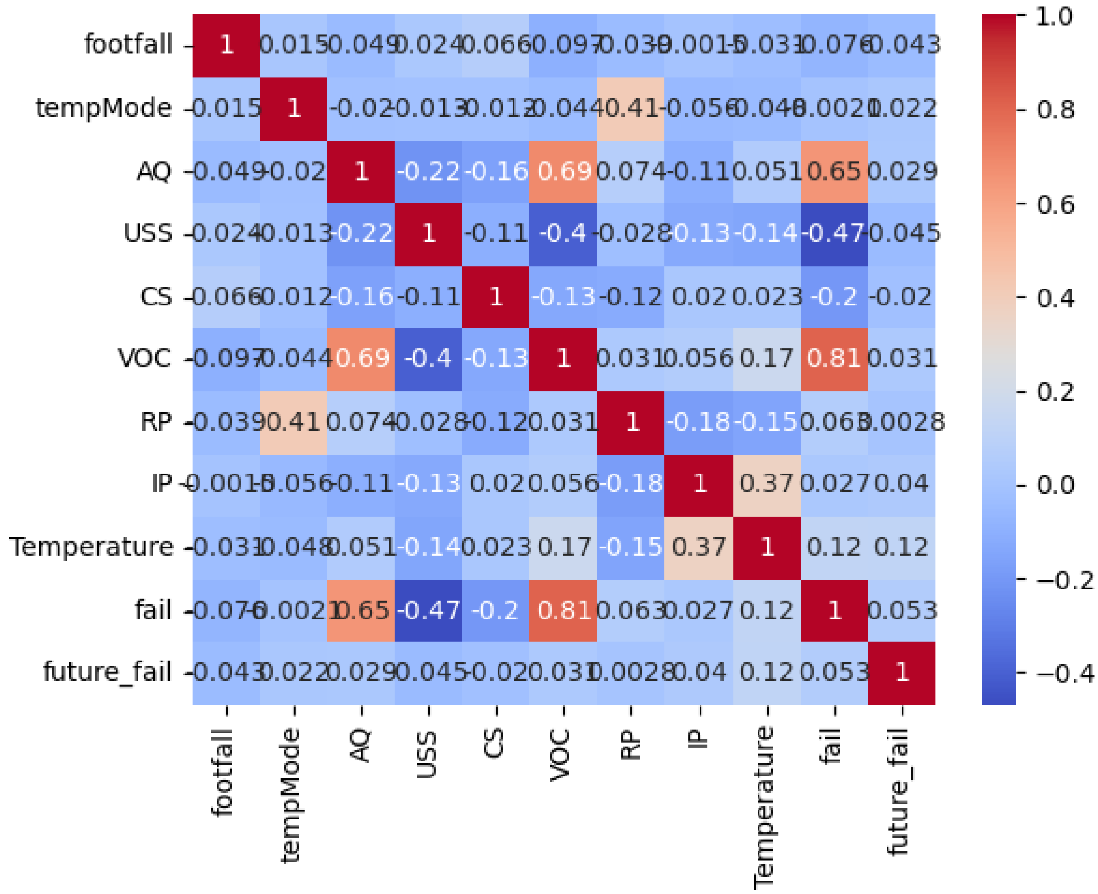
```
         0.0       0.62      0.74      0.68        90
         1.0       0.59      0.45      0.51        74

    accuracy                           0.61       164
   macro avg       0.60      0.60      0.59       164
weighted avg       0.61      0.61      0.60       164
```




```
ROC-AUC Score: 0.5951951951951953
```

[70]:

```
# Correlation between current variables and future failures
df_cleaned['future_fail'] = df_cleaned['fail'].shift(-1)
correlation = df_cleaned.corr()
sns.heatmap(correlation, annot=True, cmap='coolwarm')
plt.show()
```



future_fail colum has not correlation with the features therefore the model is not able to predict future values

17.2 However, I tried creating an RUL target column by implementing a counter that increments and resets to 0 whenever a failure occurs.

[71]:
```python
df_cleaned['RUL'] = 0

rul_counter = 0

for i in range(len(df_cleaned)):
    if df_cleaned.loc[i, 'fail'] == 1:
        rul_counter = 0
    else:
        rul_counter += 1


    df_cleaned.loc[i, 'RUL'] = rul_counter
```

17.3 I also created an RUL_percentage column for classification, which is related to the counter that counts the cycles after the failure.

[72]:
```
# Create a column for RUL percentage
df_cleaned['RUL_percentage'] = 0

# Variable to carry the starting index of the current interval
start_idx = 0

# Iterate over the DataFrame
for i in range(len(df_cleaned)):
    if df_cleaned.loc[i, 'fail'] == 1:  # If there is a fault
       # Calculate the range for the interval before failure
        interval_length = i - start_idx

        # Normalize RUL to 100%-0% range before failure
        if interval_length > 0:  # Avoid divisions by zero
            for j in range(start_idx, i):
                df_cleaned.loc[j, 'RUL_percentage'] = 100 - ((j - start_idx) /
 ↪interval_length) * 100

        # The fault value is 0%
        df_cleaned.loc[i, 'RUL_percentage'] = 0

        # Set the start of the next interval
        start_idx = i + 1

# Normalize data after the last failure to the end of the DataFrame
interval_length = len(df_cleaned) - start_idx
if interval_length > 0:
    for j in range(start_idx, len(df_cleaned)):
        df_cleaned.loc[j, 'RUL_percentage'] = 100 - ((j - start_idx) /
 ↪interval_length) * 100

# Check the results
print(df_cleaned[['RUL', 'RUL_percentage', 'fail']])
```

```
     RUL  RUL_percentage  fail
0      1           100.0     0
1      0             0.0     1
2      0             0.0     1
3      1           100.0     0
4      2            50.0     0
..   …               …    …
812    0             0.0     1
813    0             0.0     1
814    0             0.0     1
815    0             0.0     1
```

```
816    0            0.0     1

[817 rows x 3 columns]

/tmp/ipykernel_2392/257230536.py:16: FutureWarning: Setting an item of
incompatible dtype is deprecated and will raise in a future error of pandas.
Value '83.33333333333334' has dtype incompatible with int64, please explicitly
cast to a compatible dtype first.
  df_cleaned.loc[j, 'RUL_percentage'] = 100 - ((j - start_idx) /
interval_length) * 100
```

[73]:

```python
# Define the conditions for categorizing
conditions = [
    (df_cleaned['RUL_percentage'] >= 75),  # 75% o más
    (df_cleaned['RUL_percentage'] >= 50) & (df_cleaned['RUL_percentage'] < 75),␣
 ↪ # 50% - 75%
    (df_cleaned['RUL_percentage'] >= 25) & (df_cleaned['RUL_percentage'] < 50),␣
 ↪ # 25% - 50%
    (df_cleaned['RUL_percentage'] < 25)  # Menor de 25%
]

# Define the corresponding categories
categories = ['75-100%', '50-75%', '25-50%', '0-25%']

# Assign category according to conditions
df_cleaned['RUL_category'] = np.select(conditions, categories,␣
 ↪default='Unknown')

# Check the result
print(df_cleaned[['RUL_percentage', 'RUL_category']].head())
```

```
   RUL_percentage RUL_category
0           100.0      75-100%
1             0.0        0-25%
2             0.0        0-25%
3           100.0      75-100%
4            50.0       50-75%
```

[74]:

```python
# Check for out-of-range values
print(df_cleaned[df_cleaned['RUL_percentage'] < 0])
print(df_cleaned[df_cleaned['RUL_percentage'] > 100])
```

```
Empty DataFrame
Columns: [footfall, tempMode, AQ, USS, CS, VOC, RP, IP, Temperature, fail,
future_fail, RUL, RUL_percentage, RUL_category]
Index: []
Empty DataFrame
Columns: [footfall, tempMode, AQ, USS, CS, VOC, RP, IP, Temperature, fail,
```

```
future_fail, RUL, RUL_percentage, RUL_category]
Index: []
```

[ ]:

```

```

[75]:

```python
df_cleaned.RUL.value_counts()
```

[75]:

```
RUL
0     370
1     192
2     110
3      58
4      35
5      25
6      11
7       7
8       6
9       2
10      1
Name: count, dtype: int64
```

[76]:

```python
# Split the data into features (X) and label (y)
X = df_cleaned.drop(columns=['fail', 'RUL', 'future_fail', 'RUL_percentage',␣
↪'RUL_category'])
y = df_cleaned['RUL_category']

# Split the data into training and testing

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1,␣
↪random_state=42, stratify=y)
```

[77]:

```python
# Initialize the encoder
label_encoder = LabelEncoder()

# Encode the categories
y_train_encoded = label_encoder.fit_transform(y_train)
y_test_encoded = label_encoder.transform(y_test)
```

[78]:

```python
scaler = StandardScaler()

# Adjusting and transforming training characteristics
X_train_scaled = scaler.fit_transform(X_train)

# Transforming test features
X_test_scaled = scaler.transform(X_test)
```

18 Training

[79]:
```python
# Initialize the model
classifier = RandomForestClassifier(
    n_estimators=100,
    random_state=42,
    n_jobs=-1
)

# Training
classifier.fit(X_train_scaled, y_train_encoded)
```

[79]:
```
RandomForestClassifier(n_jobs=-1, random_state=42)
```

19 Calculate better parameters for the RandomForestClassifier

[80]:
```python
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 15, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

grid_search = GridSearchCV(RandomForestClassifier(random_state=42), param_grid,␣
  ↪cv=5)
grid_search.fit(X_train_scaled, y_train_encoded)

print("Mejores parámetros:", grid_search.best_params_)

best_model = grid_search.best_estimator_
y_pred = best_model.predict(X_test_scaled)
accuracy = accuracy_score(y_test_encoded, y_pred)
print(f"Accuracy después del ajuste: {accuracy:.2f}")
```

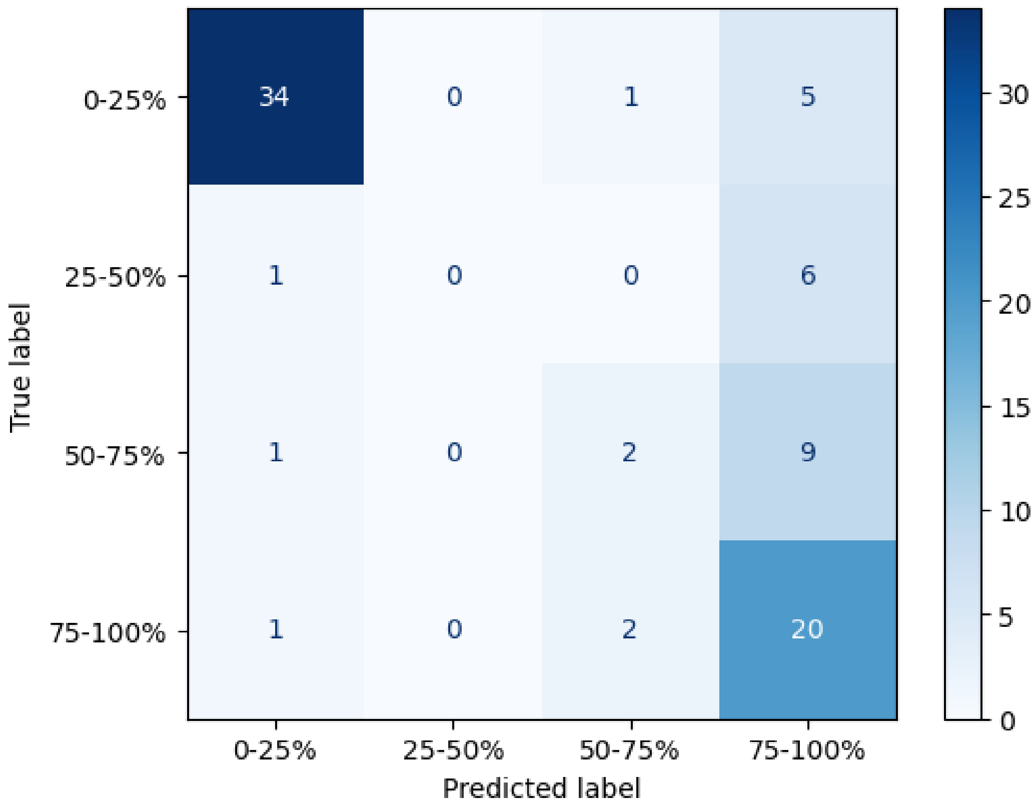
```
Mejores parámetros: {'max_depth': 15, 'min_samples_leaf': 4,
'min_samples_split': 2, 'n_estimators': 100}
Accuracy después del ajuste: 0.67
```

[81]:
```python
y_pred = classifier.predict(X_test_scaled)
accuracy = accuracy_score(y_test_encoded, y_pred)
print(f"Accuracy: {accuracy:.2f}")

print("\nClassification Report:")
print(classification_report(y_test_encoded, y_pred, target_names=label_encoder.
  ↪classes_))
```

```python
cm = confusion_matrix(y_test_encoded, y_pred)
print("\nConfusion Matrix:")
print(cm)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_encoder.
  ↪classes_)
disp.plot(cmap='Blues')
plt.show()
```

```
Accuracy: 0.68

Classification Report:
              precision    recall  f1-score   support

       0-25%       0.92      0.85      0.88        40
      25-50%       0.00      0.00      0.00         7
      50-75%       0.40      0.17      0.24        12
     75-100%       0.50      0.87      0.63        23

    accuracy                           0.68        82
   macro avg       0.45      0.47      0.44        82
weighted avg       0.65      0.68      0.64        82


Confusion Matrix:
[[34  0  1  5]
 [ 1  0  0  6]
 [ 1  0  2  9]
 [ 1  0  2 20]]
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1469:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/opt/conda/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1469:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/opt/conda/lib/python3.10/site-packages/sklearn/metrics/_classification.py:1469:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



[82]:

```
# Change models
model1 = RandomForestClassifier(n_estimators=100, random_state=42)
model2 = XGBClassifier(n_estimators=100, random_state=42)
model3 = SVC(kernel='linear', random_state=42)

ensemble_model = VotingClassifier(estimators=[('rf', model1), ('xgb', model2),␣
 ↪('svm', model3)], voting='hard')
ensemble_model.fit(X_train_scaled, y_train_encoded)

# Predictions
y_pred = ensemble_model.predict(X_test_scaled)
accuracy = accuracy_score(y_test_encoded, y_pred)
print(f"Accuracy del modelo en conjunto: {accuracy:.2f}")
```

```
Accuracy del modelo en conjunto: 0.68
```

[ ]:

[83]:

```
df_cleaned['RUL'] = 0

rul_counter = 0
```

```
for i in range(len(df_cleaned)):
    if df_cleaned.loc[i, 'fail'] == 1:
        rul_counter = 0
    else:
        rul_counter += 1

    df_cleaned.loc[i, 'RUL'] = rul_counter
```

[84]:

```
print(df_cleaned[['fail', 'RUL','RUL_percentage']].head(20))
#df_cleaned.head(25)
```

```
    fail  RUL  RUL_percentage
0      0    1      100.000000
1      1    0        0.000000
2      1    0        0.000000
3      0    1      100.000000
4      0    2       50.000000
5      1    0        0.000000
6      1    0        0.000000
7      0    1      100.000000
8      1    0        0.000000
9      0    1      100.000000
10     0    2       83.333333
11     0    3       66.666667
12     0    4       50.000000
13     0    5       33.333333
14     0    6       16.666667
15     1    0        0.000000
16     1    0        0.000000
17     1    0        0.000000
18     0    1      100.000000
19     0    2       50.000000
```

[ ]:

```

```

[85]:

```
counts = df_cleaned['RUL_percentage'].value_counts()
valid_rul = counts[counts > 1].index
df_cleaned_filtered = df_cleaned[df_cleaned['RUL_percentage'].isin(valid_rul)]
```

[86]:

```
X = df_cleaned_filtered.drop(columns=['fail',␣
 ↪'RUL','future_fail','RUL_percentage','RUL_category'])#,'cycle_id'])  #␣
 ↪Sensores como entrada
y = df_cleaned_filtered['RUL_percentage']  # RUL como objetivo
# X = df_cleaned_filtered.drop(columns=['fail',␣
 ↪'RUL','future_fail'])#,'cycle_id'])  # Sensores como entrada
# y = df_cleaned_filtered['RUL']  # RUL como objetivo
```

[87]:
```python
y.value_counts()
```

[87]:
```
RUL_percentage
0.000000      370
100.000000    192
50.000000      71
66.666667      28
33.333333      28
40.000000      15
60.000000      15
80.000000      15
20.000000      15
25.000000      14
75.000000      14
62.500000       4
37.500000       4
12.500000       4
87.500000       4
16.666667       4
83.333333       4
Name: count, dtype: int64
```

[88]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42, stratify=y)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪stratify=y)
```

[89]:
```python
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[90]:
```python
rul_scaler = MinMaxScaler()
y_train_scaled = rul_scaler.fit_transform(y_train.values.reshape(-1, 1))
y_test_scaled = rul_scaler.transform(y_test.values.reshape(-1, 1))

y_pred_original = rul_scaler.inverse_transform(y_pred.reshape(-1, 1))
```

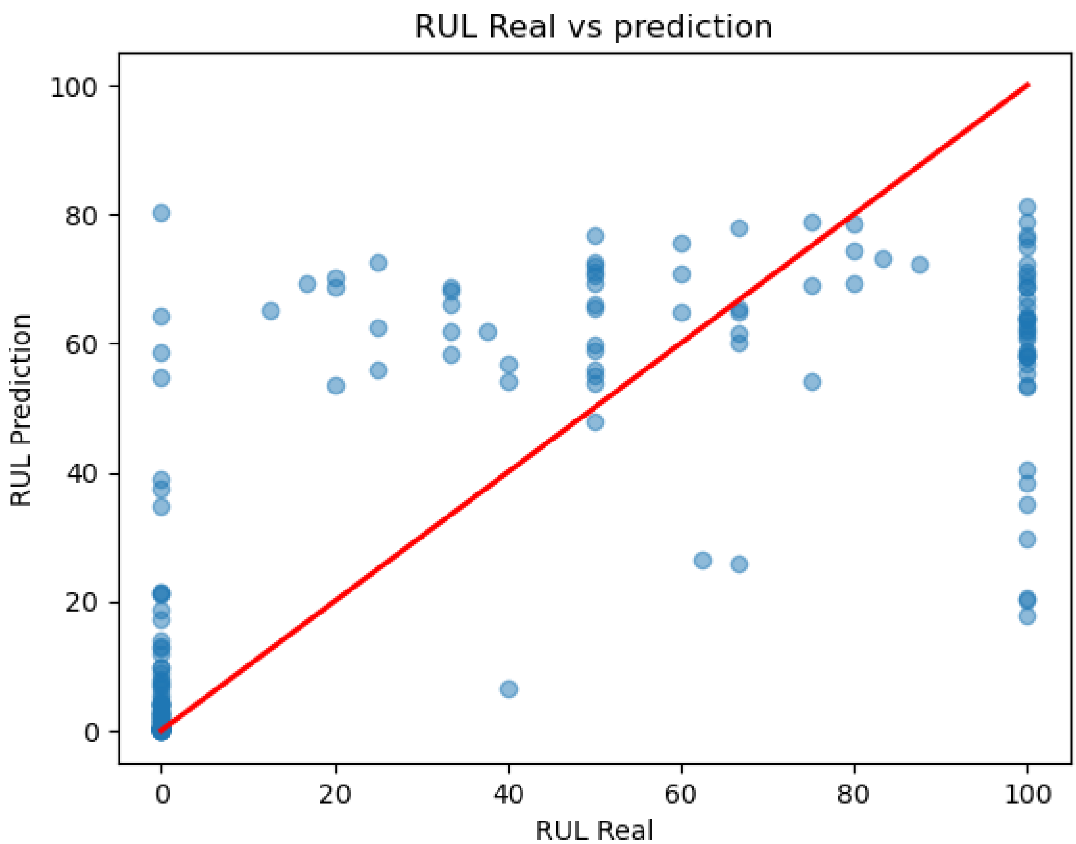
[91]:
```python
model = RandomForestRegressor(
    n_estimators=300,
    min_samples_split=10,
    min_samples_leaf=4,
    max_depth=10,
    random_state=42
)
model.fit(X_train_scaled, y_train_scaled)

y_pred_scaled = model.predict(X_test_scaled)
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/base.py:1151:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples,), for example using
ravel().
  return fit_method(estimator, *args, **kwargs)
```

[92]:
```
y_test_original = rul_scaler.inverse_transform(y_test_scaled.reshape(-1, 1))
y_pred_original = rul_scaler.inverse_transform(y_pred_scaled.reshape(-1, 1))

mae = mean_absolute_error(y_test_original, y_pred_original)
rmse = mean_squared_error(y_test_original, y_pred_original, squared=False)
r2 = r2_score(y_test_original, y_pred_original)

print(f"MAE: {mae:.2f}")
print(f"RMSE: {rmse:.2f}")
print(f"R²: {r2:.2f}")
```

```
MAE: 20.21
RMSE: 28.61
R²: 0.53
```

[93]:
```
plt.scatter(y_test_original, y_pred_original, alpha=0.5)
plt.plot([y_test_original.min(), y_test_original.max()],
         [y_test_original.min(), y_test_original.max()], color='red',␣
 ↪linewidth=2)
plt.xlabel("RUL Real")
plt.ylabel("RUL Prediction")
plt.title("RUL Real vs prediction")
plt.show()
```



[94]:
```
class DNN(nn.Module):
    def __init__(self, input_size):
        super(DNN, self).__init__()
        self.model = nn.Sequential(
            nn.Linear(input_size, 256),
            nn.BatchNorm1d(256),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.Linear(256, 128),
            nn.BatchNorm1d(128),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.Linear(128, 64),
            nn.BatchNorm1d(64),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.Linear(64, 32),
            nn.BatchNorm1d(32),
            nn.ReLU(),
            nn.Linear(32, 1)
```

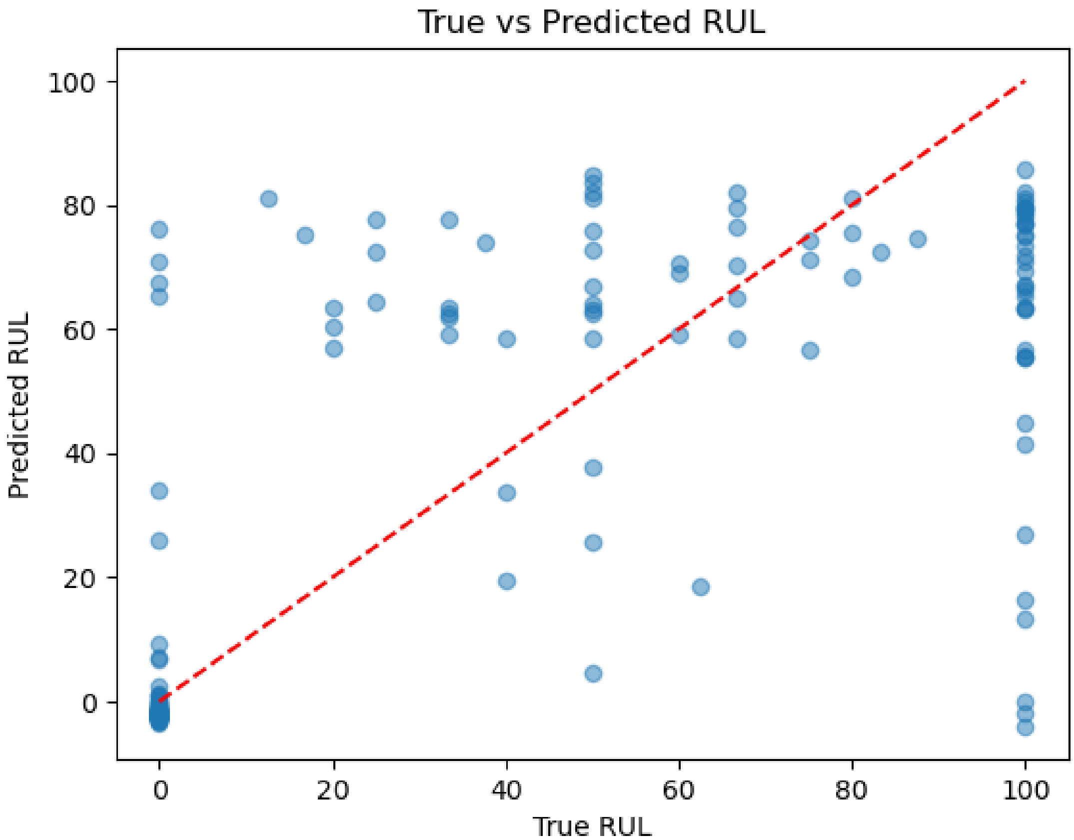
```python
        )

    def forward(self, x):
        return self.model(x)

input_size = X_train.shape[1]
model = DNN(input_size)
criterion = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.1)

from torch.utils.data import DataLoader, TensorDataset


X_train_tensor = torch.tensor(X_train_scaled, dtype=torch.float32)
y_train_tensor = torch.tensor(y_train_scaled, dtype=torch.float32)
train_dataset = TensorDataset(X_train_tensor, y_train_tensor)

train_loader = DataLoader(train_dataset, batch_size=128)#, shuffle=True)

# training
num_epochs = 100
for epoch in range(num_epochs):
    model.train()
    epoch_loss = 0
    for batch_X, batch_y in train_loader:
        optimizer.zero_grad()
        predictions = model(batch_X)
        loss = criterion(predictions, batch_y)
        loss.backward()
        optimizer.step()
        epoch_loss += loss.item()

    print(f"Epoch {epoch+1}/{num_epochs}, Loss: {epoch_loss/len(train_loader):.
↪4f}")

model.eval()
with torch.no_grad():
    X_test_tensor = torch.tensor(X_test_scaled, dtype=torch.float32)
    y_test_tensor = torch.tensor(y_test_scaled, dtype=torch.float32)


    predictions_scaled = model(X_test_tensor).detach().numpy()


    predictions_original = rul_scaler.inverse_transform(predictions_scaled)
    y_test_original = rul_scaler.inverse_transform(y_test_scaled)
```

```
    mae = mean_absolute_error(y_test_original, predictions_original)
    rmse = mean_squared_error(y_test_original, predictions_original,␣
↪squared=False)
    r2 = r2_score(y_test_original, predictions_original)

    print(f"MAE: {mae:.2f}")
    print(f"RMSE: {rmse:.2f}")
    print(f"R²: {r2:.2f}")

    import matplotlib.pyplot as plt
    plt.scatter(y_test_original, predictions_original, alpha=0.5)
    plt.plot([y_test_original.min(), y_test_original.max()],
             [y_test_original.min(), y_test_original.max()],
             color='red', linestyle='--')
    plt.xlabel("True RUL")
    plt.ylabel("Predicted RUL")
    plt.title("True vs Predicted RUL")
    plt.show()
```

```
Epoch 1/100, Loss: 0.8678
Epoch 2/100, Loss: 0.4084
Epoch 3/100, Loss: 0.2029
Epoch 4/100, Loss: 0.1629
Epoch 5/100, Loss: 0.1603
Epoch 6/100, Loss: 0.1291
Epoch 7/100, Loss: 0.1176
Epoch 8/100, Loss: 0.1033
Epoch 9/100, Loss: 0.0933
Epoch 10/100, Loss: 0.0860
Epoch 11/100, Loss: 0.0824
Epoch 12/100, Loss: 0.0807
Epoch 13/100, Loss: 0.0802
Epoch 14/100, Loss: 0.0759
Epoch 15/100, Loss: 0.0761
Epoch 16/100, Loss: 0.0727
Epoch 17/100, Loss: 0.0757
Epoch 18/100, Loss: 0.0743
Epoch 19/100, Loss: 0.0723
Epoch 20/100, Loss: 0.0731
Epoch 21/100, Loss: 0.0729
Epoch 22/100, Loss: 0.0700
Epoch 23/100, Loss: 0.0699
Epoch 24/100, Loss: 0.0701
Epoch 25/100, Loss: 0.0714
Epoch 26/100, Loss: 0.0680
Epoch 27/100, Loss: 0.0688
Epoch 28/100, Loss: 0.0664
```

```
Epoch 29/100, Loss: 0.0665
Epoch 30/100, Loss: 0.0694
Epoch 31/100, Loss: 0.0684
Epoch 32/100, Loss: 0.0671
Epoch 33/100, Loss: 0.0657
Epoch 34/100, Loss: 0.0661
Epoch 35/100, Loss: 0.0664
Epoch 36/100, Loss: 0.0632
Epoch 37/100, Loss: 0.0663
Epoch 38/100, Loss: 0.0635
Epoch 39/100, Loss: 0.0649
Epoch 40/100, Loss: 0.0600
Epoch 41/100, Loss: 0.0646
Epoch 42/100, Loss: 0.0641
Epoch 43/100, Loss: 0.0635
Epoch 44/100, Loss: 0.0599
Epoch 45/100, Loss: 0.0619
Epoch 46/100, Loss: 0.0597
Epoch 47/100, Loss: 0.0641
Epoch 48/100, Loss: 0.0581
Epoch 49/100, Loss: 0.0631
Epoch 50/100, Loss: 0.0637
Epoch 51/100, Loss: 0.0575
Epoch 52/100, Loss: 0.0615
Epoch 53/100, Loss: 0.0620
Epoch 54/100, Loss: 0.0601
Epoch 55/100, Loss: 0.0574
Epoch 56/100, Loss: 0.0554
Epoch 57/100, Loss: 0.0637
Epoch 58/100, Loss: 0.0580
Epoch 59/100, Loss: 0.0602
Epoch 60/100, Loss: 0.0558
Epoch 61/100, Loss: 0.0558
Epoch 62/100, Loss: 0.0564
Epoch 63/100, Loss: 0.0583
Epoch 64/100, Loss: 0.0596
Epoch 65/100, Loss: 0.0540
Epoch 66/100, Loss: 0.0577
Epoch 67/100, Loss: 0.0556
Epoch 68/100, Loss: 0.0551
Epoch 69/100, Loss: 0.0537
Epoch 70/100, Loss: 0.0540
Epoch 71/100, Loss: 0.0534
Epoch 72/100, Loss: 0.0523
Epoch 73/100, Loss: 0.0550
Epoch 74/100, Loss: 0.0513
Epoch 75/100, Loss: 0.0537
Epoch 76/100, Loss: 0.0541
```

```
Epoch 77/100, Loss: 0.0516
Epoch 78/100, Loss: 0.0535
Epoch 79/100, Loss: 0.0511
Epoch 80/100, Loss: 0.0497
Epoch 81/100, Loss: 0.0520
Epoch 82/100, Loss: 0.0499
Epoch 83/100, Loss: 0.0503
Epoch 84/100, Loss: 0.0553
Epoch 85/100, Loss: 0.0556
Epoch 86/100, Loss: 0.0525
Epoch 87/100, Loss: 0.0523
Epoch 88/100, Loss: 0.0507
Epoch 89/100, Loss: 0.0503
Epoch 90/100, Loss: 0.0471
Epoch 91/100, Loss: 0.0485
Epoch 92/100, Loss: 0.0465
Epoch 93/100, Loss: 0.0465
Epoch 94/100, Loss: 0.0468
Epoch 95/100, Loss: 0.0526
Epoch 96/100, Loss: 0.0476
Epoch 97/100, Loss: 0.0499
Epoch 98/100, Loss: 0.0518
Epoch 99/100, Loss: 0.0518
Epoch 100/100, Loss: 0.0532
MAE: 19.43
RMSE: 30.04
R²: 0.48
```


True vs Predicted RUL
Predicted RUL
True RUL
100
80
60
40
20
0
0
20
40
60
80
100