# databricks Theophilus_Ebode_ml

(https://databricks.com)

```
# To import mlflow and autolog machine learning runs
import mlflow
mlflow.pyspark.ml.autolog()
```

```
# The FaultDataset in DBFS
dbutils.fs.ls("/FileStore/tables/")
```

```
Out[2]: [FileInfo(path='dbfs:/FileStore/tables/FaultDataset.csv', name='FaultDataset.csv', size=1703184, modificationTime
=1678589742000),
 FileInfo(path='dbfs:/FileStore/tables/Occupancy_Detection_Data.csv', name='Occupancy_Detection_Data.csv', size=50968, mo
dificationTime=1677673883000),
 FileInfo(path='dbfs:/FileStore/tables/account-models/', name='account-models/', size=0, modificationTime=0),
 FileInfo(path='dbfs:/FileStore/tables/accounts/', name='accounts/', size=0, modificationTime=0),
 FileInfo(path='dbfs:/FileStore/tables/accounts.zip', name='accounts.zip', size=5297592, modificationTime=1675260543000),
 FileInfo(path='dbfs:/FileStore/tables/activations/', name='activations/', size=0, modificationTime=0),
 FileInfo(path='dbfs:/FileStore/tables/activations.zip', name='activations.zip', size=8411369, modificationTime=167525765
4000),
 FileInfo(path='dbfs:/FileStore/tables/clinicaltrial_2019/', name='clinicaltrial_2019/', size=0, modificationTime=0),
 FileInfo(path='dbfs:/FileStore/tables/clinicaltrial_2019.csv', name='clinicaltrial_2019.csv', size=42400056, modificatio
nTime=1679426915000),
 FileInfo(path='dbfs:/FileStore/tables/clinicaltrial_2019.zip', name='clinicaltrial_2019.zip', size=9707871, modification
Time=1678924265000),
 FileInfo(path='dbfs:/FileStore/tables/clinicaltrial_2020/', name='clinicaltrial_2020/', size=0, modificationTime=0),
 FileInfo(path='dbfs:/FileStore/tables/clinicaltrial_2020.csv', name='clinicaltrial_2020.csv', size=46318151, modificatio
nTime=1679431882000),
 FileInfo(path='dbfs:/FileStore/tables/clinicaltrial_2020.zip', name='clinicaltrial_2020.zip', size=10599182, modificatio
nTime=1678915950000),
 FileInfo(path='dbfs:/FileStore/tables/clinicaltrial_2021/', name='clinicaltrial_2021/', size=0, modificationTime=0),
```

```
# To read the data we want to work with into spark DataFrame
FaultsDF = spark.read.csv("/FileStore/tables/FaultDataset.csv",
                         header = "true",
                         inferSchema = "true")
```

```
# To have an overview of what the data looks like
FaultsDF.display()
```

Table

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.3503125 | 0.3496875 | 0.35 | 0.3459375 | 0.3475 | 0.3459375 | 0.341875 | 0.3434375 | 0.355 |
| 2 | 0.5090625 | 0.484375 | 0.046875 | 0.071875 | 0.06 | 0.0634375 | 0.0575 | 0.0546875 | 0.0559375 |
| 3 | 0.0928125 | 0.0975 | 0.1096875 | 0.1025 | 0.09625 | 0.1053125 | 0.09875 | 0.098125 | 0.091875 |
| 4 | 0.09375 | 0.089375 | 0.091875 | 0.0996875 | 0.0909375 | 0.096875 | 0.0940625 | 0.096875 | 0.096875 |
| 5 | 0.036875 | 0.0440625 | 0.038125 | 0.0428125 | 0.0353125 | 0.0340625 | 0.033125 | 0.0403125 | 0.0346875 |
| 6 | 0.135625 | 0.3034375 | 0.13875 | 0.140625 | 0.126875 | 0.130625 | 0.139375 | 0.143125 | 0.1290625 |
| 7 | 0.3446875 | 0.35125 | 0.3353125 | 0.3471875 | 0.34625 | 0.348125 | 0.3478125 | 0.3521875 | 0.3525 |

9,292 rows

```
#To convert to pandas dataframe so that we can perform some EDA and visualisations
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
```

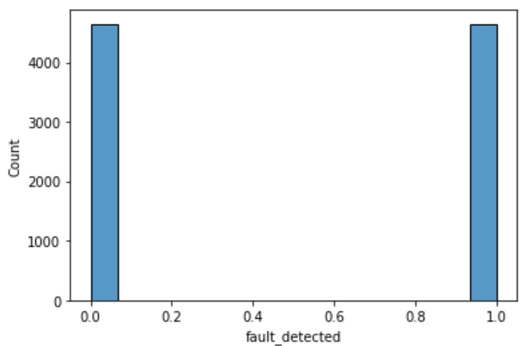
```
# To convert FaultsDF To pandas dataframe
FaultPandasFrame = FaultsDF.toPandas()
```

```
# To see the first five rows in the data
FaultPandasFrame.head()
```

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.350313 | 0.349687 | 0.350000 | 0.345938 | 0.347500 | 0.345938 | 0.341875 | 0.343438 | 0.355000 | 0.355312 | 0.345938 | 0.352500 | 0.357500 | 0.359063 | 0.358750 |
| **1** | 0.509062 | 0.484375 | 0.046875 | 0.071875 | 0.060000 | 0.063437 | 0.057500 | 0.054688 | 0.055938 | 0.058125 | 0.062812 | 0.065625 | 0.064062 | 0.063437 | 0.053437 |
| **2** | 0.092813 | 0.097500 | 0.109687 | 0.102500 | 0.096250 | 0.105313 | 0.098750 | 0.098125 | 0.091875 | 0.090938 | 0.098750 | 0.103125 | 0.100000 | 0.103438 | 0.101562 |
| **3** | 0.093750 | 0.089375 | 0.091875 | 0.099687 | 0.090938 | 0.096875 | 0.094062 | 0.096875 | 0.096875 | 0.099375 | 0.099375 | 0.095937 | 0.095937 | 0.094062 | 0.091250 |
| **4** | 0.036875 | 0.044062 | 0.038125 | 0.042813 | 0.035312 | 0.034063 | 0.033125 | 0.040313 | 0.034688 | 0.036875 | 0.035625 | 0.036250 | 0.040938 | 0.039375 | 0.035000 |

```
# To see the class balance using a histogram plot.
# The result shows that we have a balance class between fault detected or not
sns.histplot(FaultPandasFrame, x ='fault_detected')
```

```
Out[8]: <AxesSubplot:xlabel='fault_detected', ylabel='Count'>
```




```
FaultPandasFrame.shape
```

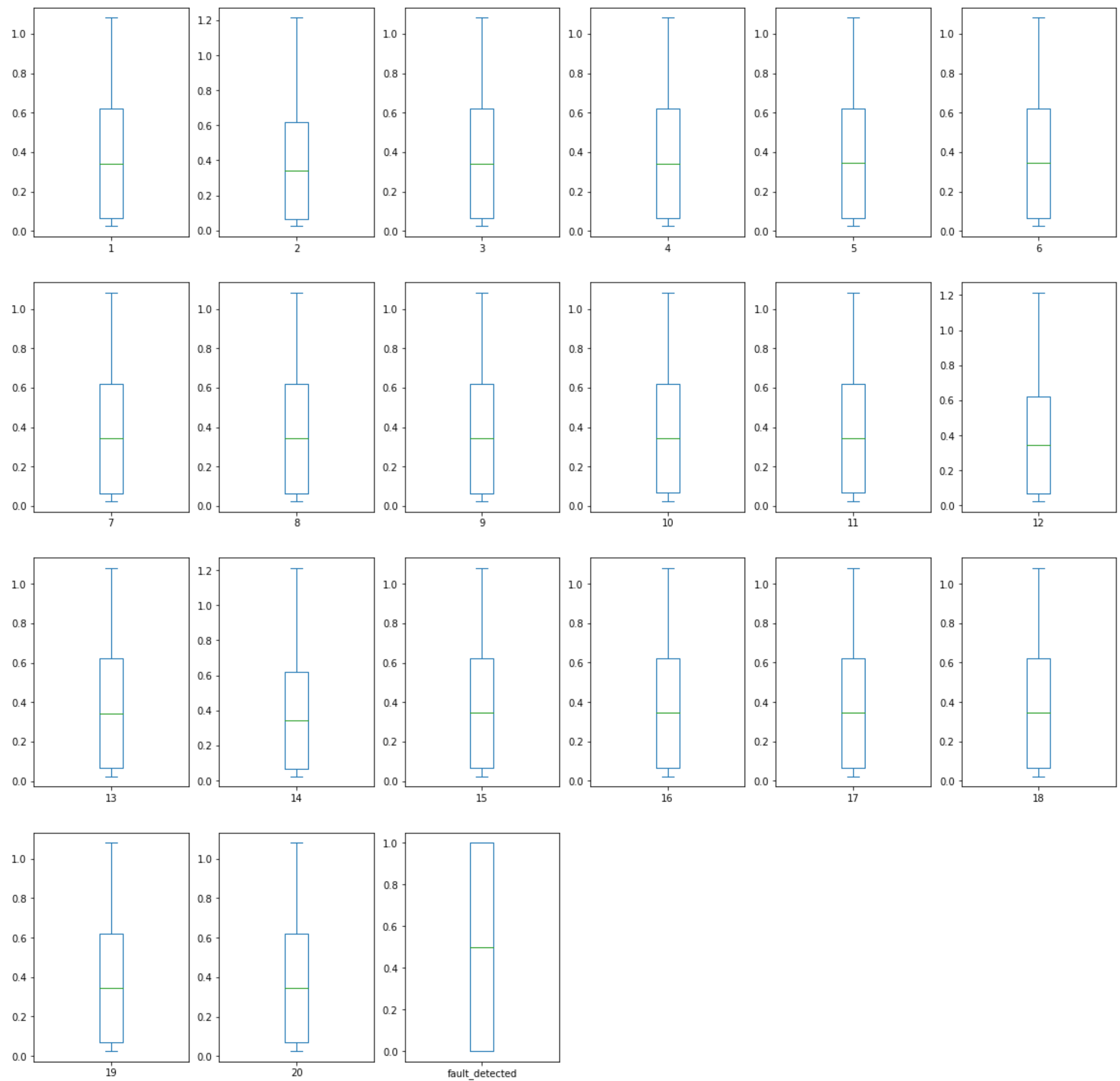
```
Out[9]: (9292, 21)
```

```
# To get a summary of the data
FaultPandasFrame.describe()
```

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 |
| **mean** | 0.341623 | 0.342631 | 0.342121 | 0.342139 | 0.342843 | 0.342828 | 0.342715 | 0.343066 | 0.343173 | 0.343925 | 0.344108 |
| **std** | 0.289195 | 0.289088 | 0.289164 | 0.289164 | 0.288965 | 0.289089 | 0.289195 | 0.289192 | 0.289340 | 0.289012 | 0.289200 |
| **min** | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 |
| **25%** | 0.064062 | 0.064609 | 0.064375 | 0.064375 | 0.065000 | 0.065000 | 0.064687 | 0.065312 | 0.065000 | 0.065937 | 0.066172 |
| **50%** | 0.342187 | 0.343750 | 0.342813 | 0.342031 | 0.343594 | 0.343750 | 0.342813 | 0.343125 | 0.342813 | 0.345000 | 0.345313 |
| **75%** | 0.618437 | 0.619062 | 0.619062 | 0.619062 | 0.619062 | 0.619062 | 0.619141 | 0.619687 | 0.619766 | 0.620000 | 0.620313 |
| **max** | 1.080938 | 1.213437 | 1.080938 | 1.080938 | 1.080938 | 1.080938 | 1.080938 | 1.080938 | 1.080938 | 1.080938 | 1.080938 |

```
#Histogram plot of the various features in the data to see how the vibration sensor readings from the data are
distributed.
FaultPandasFrame.hist()
plt.gcf().set_size_inches(20,20)
plt.show()
```


```
# Using a box and whisker plot to check if there are outliers in the virbration readings
FaultPandasFrame.plot(kind='box', subplots=True, layout=(4,6))
plt.gcf().set_size_inches(20,20)
plt.show()
```



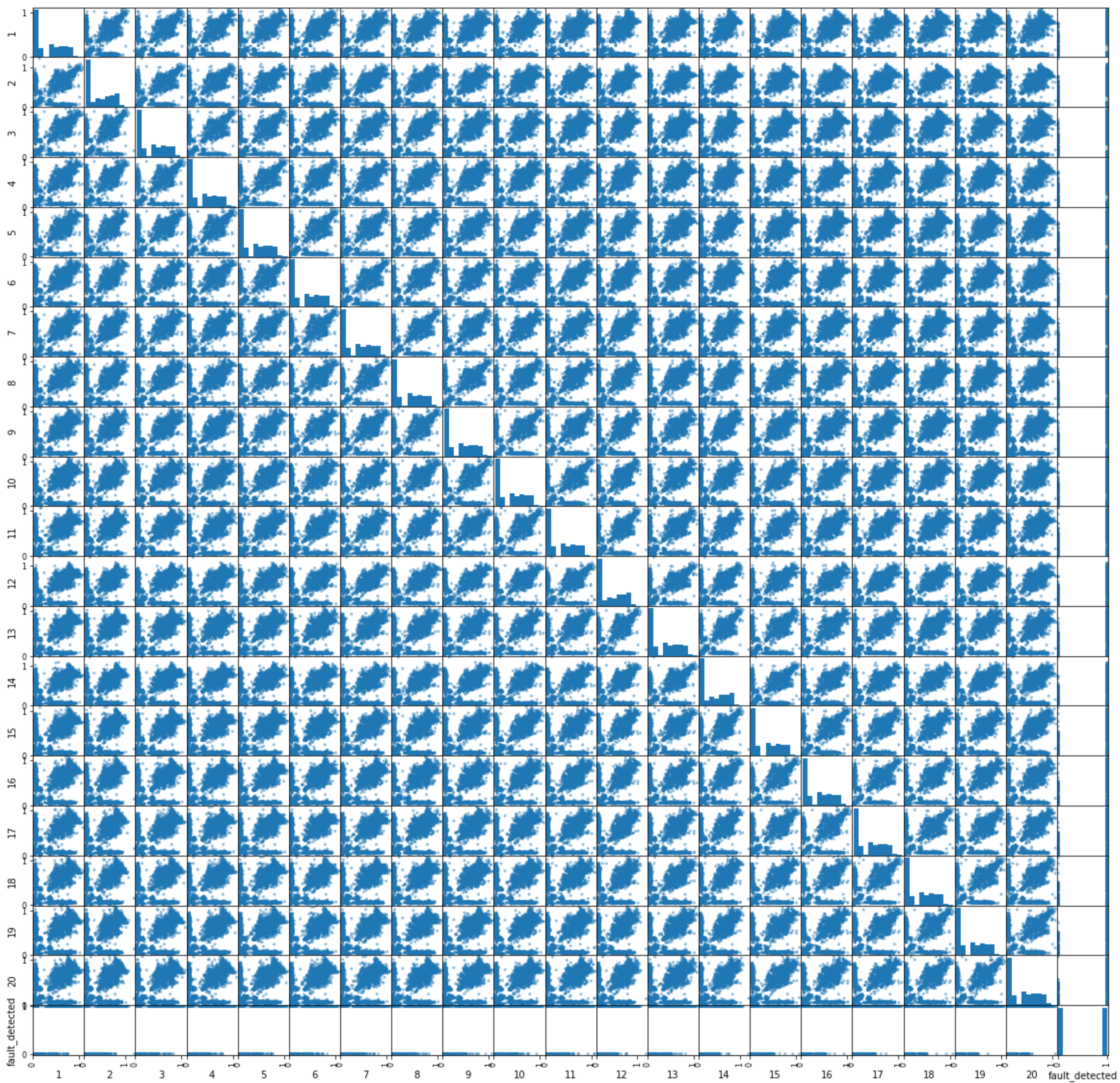

```
FaultPandasFrame.corr()
```

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 1.000000 | 0.843847 | 0.815780 | 0.826661 | 0.819727 | 0.806820 | 0.800609 | 0.800667 | 0.785560 | 0.781098 | 0.781228 | 0.772658 | 0.773191 | 0.7788 |
| **2** | 0.843847 | 1.000000 | 0.843153 | 0.813794 | 0.824917 | 0.818478 | 0.806115 | 0.799769 | 0.798175 | 0.785856 | 0.778867 | 0.780272 | 0.771881 | 0.7727 |
| **3** | 0.815780 | 0.843153 | 1.000000 | 0.844225 | 0.815464 | 0.826045 | 0.818762 | 0.806707 | 0.799662 | 0.801067 | 0.785955 | 0.780895 | 0.780712 | 0.7742 |
| **4** | 0.826661 | 0.813794 | 0.844225 | 1.000000 | 0.844152 | 0.815404 | 0.825898 | 0.821163 | 0.807515 | 0.801069 | 0.799968 | 0.786714 | 0.783222 | 0.7832 |
| **5** | 0.819727 | 0.824917 | 0.815464 | 0.844152 | 1.000000 | 0.843323 | 0.814768 | 0.827324 | 0.820063 | 0.807351 | 0.800829 | 0.801012 | 0.786438 | 0.7832 |
| **6** | 0.806820 | 0.818478 | 0.826045 | 0.815404 | 0.843323 | 1.000000 | 0.842480 | 0.813768 | 0.824977 | 0.821148 | 0.807483 | 0.799901 | 0.800890 | 0.7876 |
| **7** | 0.800609 | 0.806115 | 0.818762 | 0.825898 | 0.814768 | 0.842480 | 1.000000 | 0.844601 | 0.814972 | 0.826524 | 0.819826 | 0.807104 | 0.801846 | 0.8021 |
| **8** | 0.800667 | 0.799769 | 0.806707 | 0.821163 | 0.827324 | 0.813768 | 0.844601 | 1.000000 | 0.843669 | 0.813676 | 0.824552 | 0.819180 | 0.807114 | 0.8019 |
| **9** | 0.785560 | 0.798175 | 0.799662 | 0.807515 | 0.820063 | 0.824977 | 0.814972 | 0.843669 | 1.000000 | 0.843174 | 0.813524 | 0.825630 | 0.820179 | 0.8075 |
| **10** | 0.781098 | 0.785856 | 0.801067 | 0.801069 | 0.807351 | 0.821148 | 0.826524 | 0.813676 | 0.843174 | 1.000000 | 0.842913 | 0.812985 | 0.825341 | 0.8195 |
| **11** | 0.781228 | 0.778867 | 0.785955 | 0.799968 | 0.800829 | 0.807483 | 0.819826 | 0.824552 | 0.813524 | 0.842913 | 1.000000 | 0.842194 | 0.813314 | 0.8246 |
| **12** | 0.772658 | 0.780272 | 0.780895 | 0.786714 | 0.801012 | 0.799901 | 0.807104 | 0.819180 | 0.825630 | 0.812985 | 0.842194 | 1.000000 | 0.843725 | 0.8135 |
| **13** | 0.773191 | 0.771881 | 0.780712 | 0.783222 | 0.786438 | 0.800890 | 0.801846 | 0.807114 | 0.820179 | 0.825341 | 0.813314 | 0.843725 | 1.000000 | 0.8426 |
| **14** | 0.778808 | 0.772782 | 0.774265 | 0.783219 | 0.783206 | 0.787682 | 0.802103 | 0.801997 | 0.807529 | 0.819571 | 0.824605 | 0.813560 | 0.842642 | 1.0000 |
| **15** | 0.770734 | 0.777026 | 0.772514 | 0.774887 | 0.782338 | 0.782074 | 0.788105 | 0.800667 | 0.801262 | 0.807342 | 0.818214 | 0.825275 | 0.813118 | 0.8425 |
| **16** | 0.758679 | 0.769570 | 0.777459 | 0.774451 | 0.774300 | 0.781673 | 0.782957 | 0.788960 | 0.801438 | 0.801288 | 0.806279 | 0.819909 | 0.826241 | 0.8125 |
| **17** | 0.765337 | 0.757522 | 0.770544 | 0.780225 | 0.775226 | 0.775094 | 0.783322 | 0.782572 | 0.789297 | 0.801063 | 0.800629 | 0.807568 | 0.821294 | 0.8256 |
| **18** | 0.757268 | 0.764096 | 0.759063 | 0.771988 | 0.779908 | 0.774694 | 0.775707 | 0.783127 | 0.782368 | 0.788638 | 0.800450 | 0.801630 | 0.807897 | 0.8202 |
| **19** | 0.752535 | 0.758217 | 0.766772 | 0.761376 | 0.772765 | 0.780398 | 0.776955 | 0.777520 | 0.784443 | 0.782847 | 0.789137 | 0.802929 | 0.802816 | 0.8079 |
| **20** | 0.751781 | 0.751194 | 0.757990 | 0.766829 | 0.760875 | 0.771479 | 0.780377 | 0.776530 | 0.776484 | 0.783898 | 0.781167 | 0.788763 | 0.801218 | 0.8020 |
| **fault_detected** | 0.667028 | 0.666130 | 0.668463 | 0.670146 | 0.669696 | 0.669190 | 0.671794 | 0.673588 | 0.674972 | 0.675330 | 0.675667 | 0.677753 | 0.681194 | 0.6817 |

```
# Correlation matrix of the readings from the vibration sensors  and the fault detection
data = FaultPandasFrame
plt.figure(figsize=(20,8))
sns.heatmap(data.corr(), annot = True)
```

Out[14]: <AxesSubplot:>


```
#Scatter plot matrix to show the realtionship between two variables of the parameters being read by the vibration sensor
from pandas.plotting import scatter_matrix
scatter_matrix(FaultPandasFrame)
plt.gcf().set_size_inches(20,20)
plt.show()
```



```
df2 = FaultPandasFrame
```

```
#import pandas as pd
```

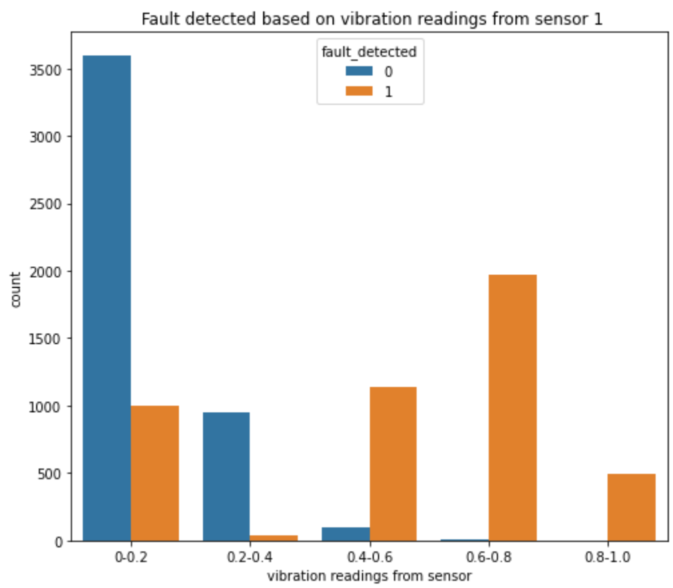
```
# We want to visualise the fault detection based on the vibration readings from each features
# To get a better visualisation, the vibration readings will be put into bins such that we capture from the minimum reading and the maximum reading
# First we can introduce a variable to hold the pandas dataframe create earlier
df = FaultPandasFrame
```

```
df.describe()
```

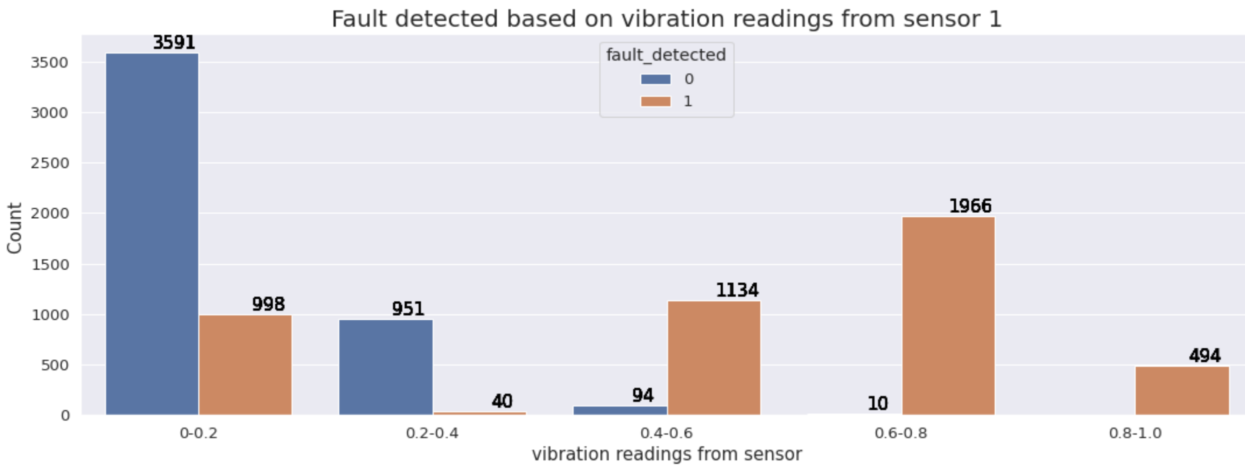
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 | 9292.000000 |
| **mean** | 0.341623 | 0.342631 | 0.342121 | 0.342139 | 0.342843 | 0.342828 | 0.342715 | 0.343066 | 0.343173 | 0.343925 | 0.344108 |
| **std** | 0.289195 | 0.289088 | 0.289164 | 0.289164 | 0.288965 | 0.289089 | 0.289195 | 0.289192 | 0.289340 | 0.289012 | 0.289200 |
| **min** | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 |
| **25%** | 0.064062 | 0.064609 | 0.064375 | 0.064375 | 0.065000 | 0.065000 | 0.064687 | 0.065312 | 0.065000 | 0.065937 | 0.066172 |
| **50%** | 0.342187 | 0.343750 | 0.342813 | 0.342031 | 0.343594 | 0.343750 | 0.342813 | 0.343125 | 0.342813 | 0.345000 | 0.345313 |
| **75%** | 0.618437 | 0.619062 | 0.619062 | 0.619062 | 0.619062 | 0.619062 | 0.619141 | 0.619687 | 0.619766 | 0.620000 | 0.620313 |
| **max** | 1.080938 | 1.213437 | 1.080938 | 1.080938 | 1.080938 | 1.080938 | 1.080938 | 1.080938 | 1.080938 | 1.080938 | 1.080938 |

```
# Putting sensor readings into bins
bin_sensor_1 = [0, 0.2, 0.4, 0.6, 0.8, 1.0]
labels =['0-0.2', '0.2-0.4', '0.4-0.6', '0.6-0.8', '0.8-1.0']
df['binned_1'] = pd.cut(df['1'], bins=bin_sensor_1 , labels =labels)
plt.figure(figsize=(8,7))
sns.countplot(x='binned_1',hue='fault_detected',  data = df)
plt.title(" Fault detected based on vibration readings from sensor 1", fontsize = 12)
plt.xlabel('vibration readings from sensor')
```

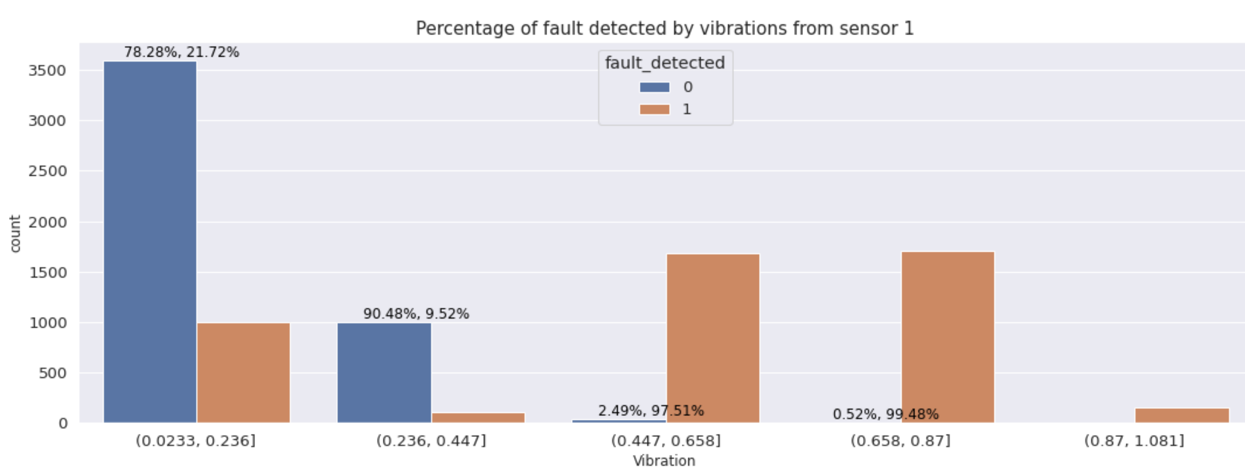
```
Out[20]: Text(0.5, 0, 'vibration readings from sensor')
```




```
plt.figure(figsize=(18,6))
sns.set(font_scale=1.2)
ax=sns.countplot(x='binned_1',hue='fault_detected',  data = df)
ax.set_title('Fault detected based on vibration readings from sensor 1' , fontsize = 20)
plt.xlabel('vibration readings from sensor', fontsize=15)
plt.ylabel('Count ', fontsize=15)
plt.xticks(rotation='horizontal')
for p in ax.patches:
    for p in ax.patches:
        ax.annotate(format(p.get_height(), '.0f'),
                    (p.get_x()+0.3, p.get_height()), ha='center', va='bottom', color='black', size=15)
```

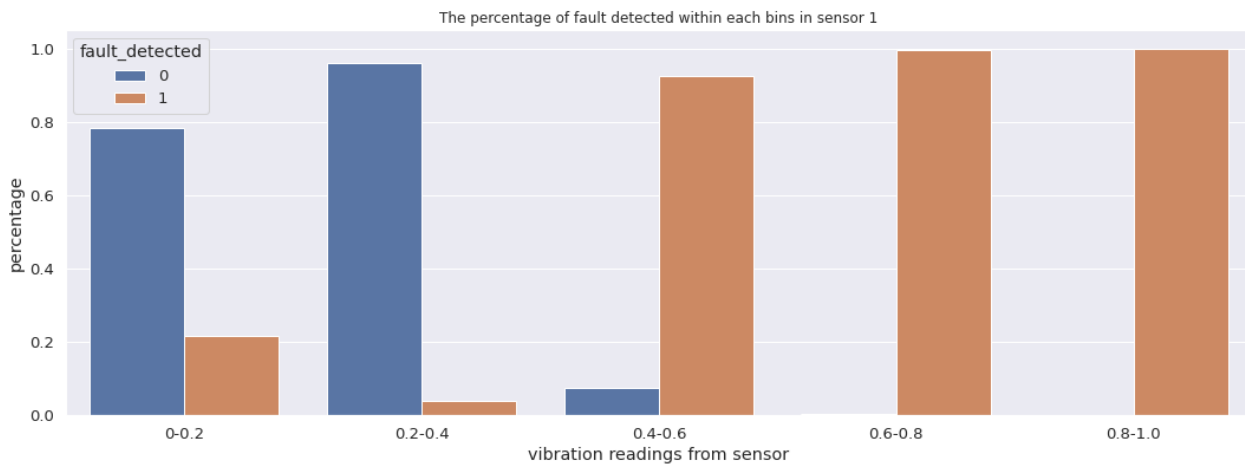



```
# Cut vibration readings inti bin and show the percenatge of fault detected within each bin
bin_sen_1 = pd.cut(df['1'], bins=5, ordered=True)
sen1_labels = [f'({interval.left}, {interval.right}]' for interval in bin_sen_1.cat.categories]
df['bins_sen_1'] = bin_sen_1.cat.rename_categories(sen1_labels )

# Create countplot
plt.figure(figsize=(18, 6))
sns.set(font_scale=1.2)
ax = sns.countplot(x='bins_sen_1',hue='fault_detected', data= df)
ax.set_title('Percentage of fault detected by vibrations from sensor 1', fontsize=15)
plt.xlabel('Vibration', fontsize=12)
plt.ylabel('count', fontsize=12)
plt.xticks(rotation='horizontal')

# Annotate plot with percentages
total_counts = df.groupby('bins_sen_1')['fault_detected'].count().reset_index(name='count')
fault_counts = df.groupby(['bins_sen_1', 'fault_detected']).size().reset_index(name='fault_count')

for p, label in zip(ax.patches, ax.get_xticklabels()):
    height = p.get_height()
    bin_label = label.get_text()
    bin_counts = fault_counts[fault_counts['bins_sen_1'] == bin_label]['fault_count']
    total_count = total_counts[total_counts['bins_sen_1'] == bin_label]['count'].iloc[0]
    percentages = [count / total_count * 100 for count in bin_counts]
    percentage_str = ', '.join([f'{percentage:.2f}%' for percentage in percentages])
    ax.annotate(percentage_str, (p.get_x() + p.get_width() / 2, height),
                ha='center', va='bottom', color='black', size=12,
                xytext=(28, 0), textcoords='offset points')

plt.show()
```



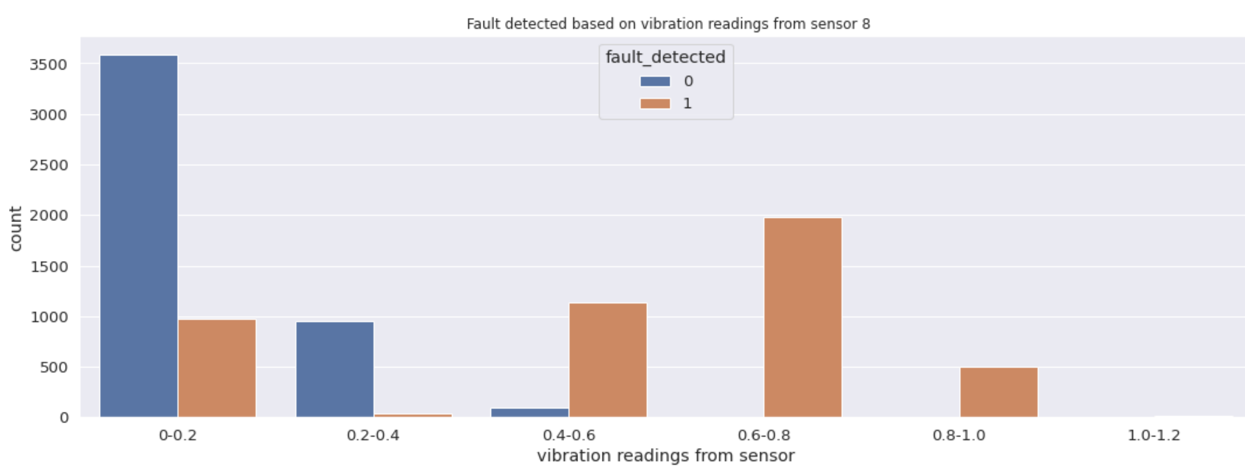
```
# The percentage of fault within each bins
bins = [0, 0.2, 0.4, 0.6, 0.8, 1.0]
labels =['0-0.2', '0.2-0.4', '0.4-0.6', '0.6-0.8', '0.8-1.0']
df['binned'] = pd.cut(df['1'], bins=bins, labels =labels)

# group by binned and calculate percentage of each fault_detected
grouped = df.groupby('binned')['fault_detected'].value_counts(normalize=True).reset_index(name='percentage')
plt.figure(figsize=(18, 6))

sns.barplot(x='binned',y ='percentage', hue='fault_detected',  data = grouped)
plt.title("The percentage of fault detected within each bins in sensor 1", fontsize = 12)
plt.xlabel('vibration readings from sensor')
```

```
Out[23]: Text(0.5, 0, 'vibration readings from sensor')
```

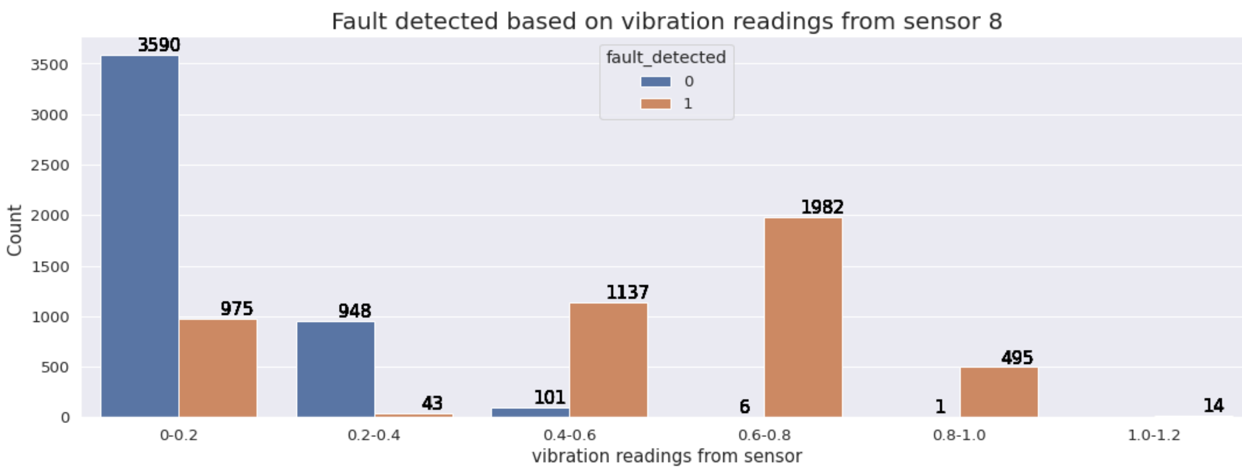



```
#Let's visualise for some other sensors. We can choose sensor 8
bins = [0, 0.2, 0.4, 0.6, 0.8, 1.0, 1.2]
labels =['0-0.2', '0.2-0.4', '0.4-0.6', '0.6-0.8', '0.8-1.0', '1.0-1.2']

df['binned'] = pd.cut(df['8'], bins=bins, labels =labels)
plt.figure(figsize=(18,6))
sns.countplot(x='binned',hue='fault_detected',  data = df)
plt.title(" Fault detected based on vibration readings from sensor 8", fontsize = 12)
plt.xlabel('vibration readings from sensor')
```

```
Out[24]: Text(0.5, 0, 'vibration readings from sensor')
```

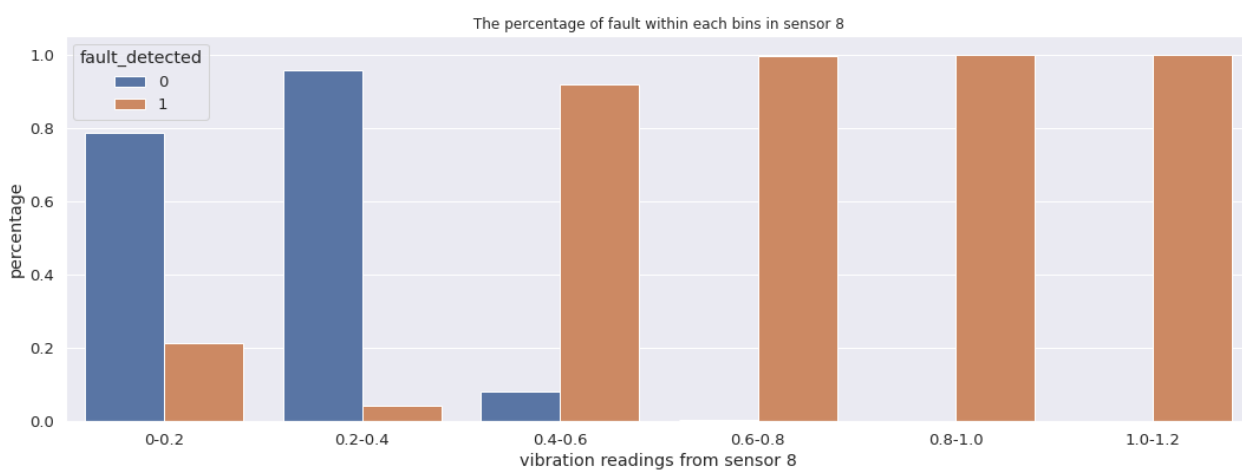


```
plt.figure(figsize=(18,6))
sns.set(font_scale=1.2)
ax=sns.countplot(x='binned',hue='fault_detected',  data = df)
ax.set_title('Fault detected based on vibration readings from sensor 8' , fontsize = 20)
plt.xlabel('vibration readings from sensor', fontsize=15)
plt.ylabel('Count ', fontsize=15)
plt.xticks(rotation='horizontal')
for p in ax.patches:
    for p in ax.patches:
        ax.annotate(format(p.get_height(), '.0f'),
                    (p.get_x()+0.3, p.get_height()), ha='center', va='bottom', color='black', size=15)
```

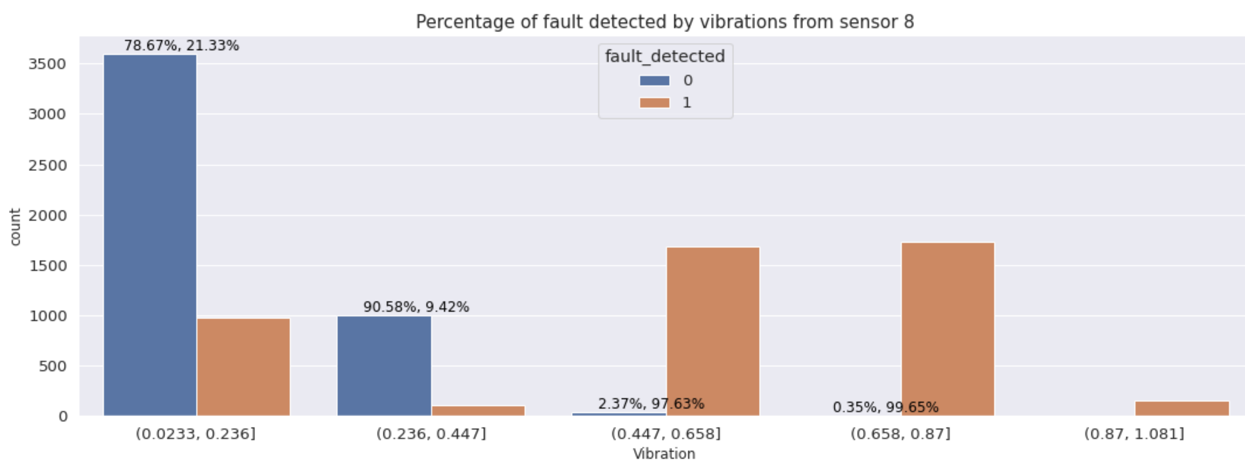



```
# The percentage of fault within each bins
#bins = [0, 0.25, 0.5, 0.75, 1.0, 1.25]
#labels =['0-0.25', '0.25-0.50', '0.50-0.75', '0.75-1.0', '1.0-1.25']
bins = [0, 0.2, 0.4, 0.6, 0.8, 1.0, 1.2]
labels =['0-0.2', '0.2-0.4', '0.4-0.6', '0.6-0.8', '0.8-1.0', '1.0-1.2']
df['binned'] = pd.cut(df['8'], bins=bins, labels =labels)
# group by binned and calculate percentage of each fault_detected
grouped = df.groupby('binned')['fault_detected'].value_counts(normalize=True).reset_index(name='percentage')

plt.figure(figsize=(18,6))
sns.barplot(x='binned',y ='percentage', hue='fault_detected',  data = grouped)
plt.title(" The percentage of fault within each bins in sensor 8 ", fontsize = 12)
plt.xlabel('vibration readings from sensor 8')
```

```
Out[26]: Text(0.5, 0, 'vibration readings from sensor 8')
```

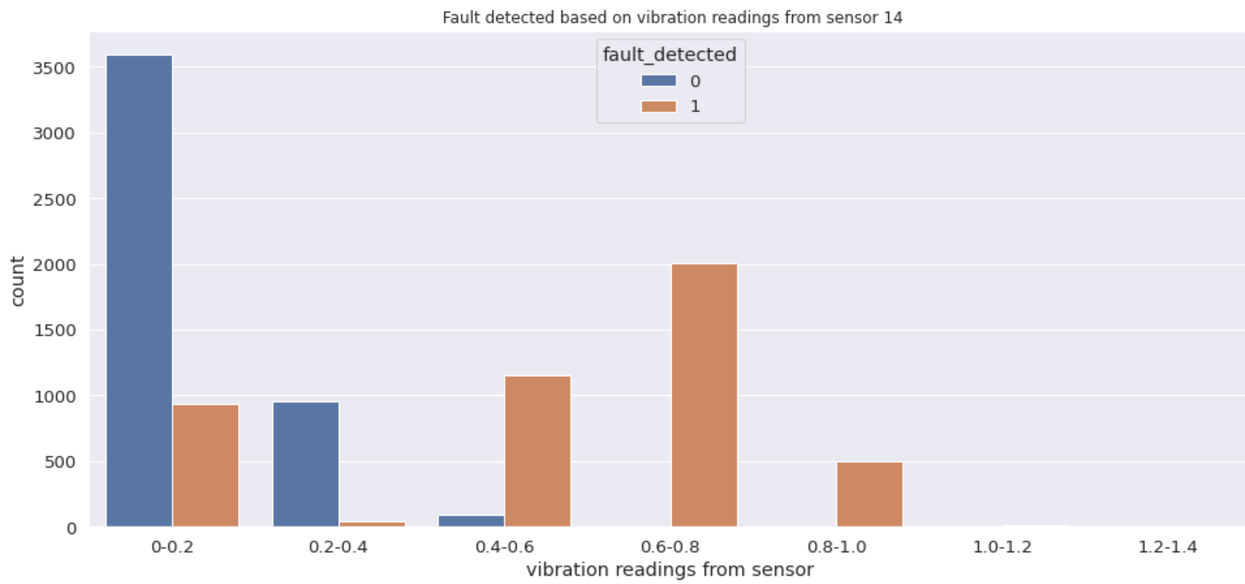


```
# Cut vibration readings inti bin and show the percenatge of fault detected within each bin
bin_sen_8 = pd.cut(df['8'], bins=5, ordered=True)
sen8_labels = [f'({interval.left}, {interval.right}]' for interval in bin_sen_8.cat.categories]
df['bins_sen_8'] = bin_sen_8.cat.rename_categories(sen8_labels )

# Create countplot
plt.figure(figsize=(18, 6))
sns.set(font_scale=1.2)
ax = sns.countplot(x='bins_sen_8',hue='fault_detected', data= df)
ax.set_title('Percentage of fault detected by vibrations from sensor 8', fontsize=15)
plt.xlabel('Vibration', fontsize=12)
plt.ylabel('count', fontsize=12)
plt.xticks(rotation='horizontal')

# Annotate plot with percentages
total_counts = df.groupby('bins_sen_8')['fault_detected'].count().reset_index(name='count')
fault_counts = df.groupby(['bins_sen_8', 'fault_detected']).size().reset_index(name='fault_count')

for p, label in zip(ax.patches, ax.get_xticklabels()):
    height = p.get_height()
    bin_label = label.get_text()
    bin_counts = fault_counts[fault_counts['bins_sen_8'] == bin_label]['fault_count']
    total_count = total_counts[total_counts['bins_sen_8'] == bin_label]['count'].iloc[0]
    percentages = [count / total_count * 100 for count in bin_counts]
    percentage_str = ', '.join([f'{percentage:.2f}%' for percentage in percentages])
    ax.annotate(percentage_str, (p.get_x() + p.get_width() / 2, height),
                ha='center', va='bottom', color='black', size=12,
                xytext=(28, 0), textcoords='offset points')

plt.show()
```

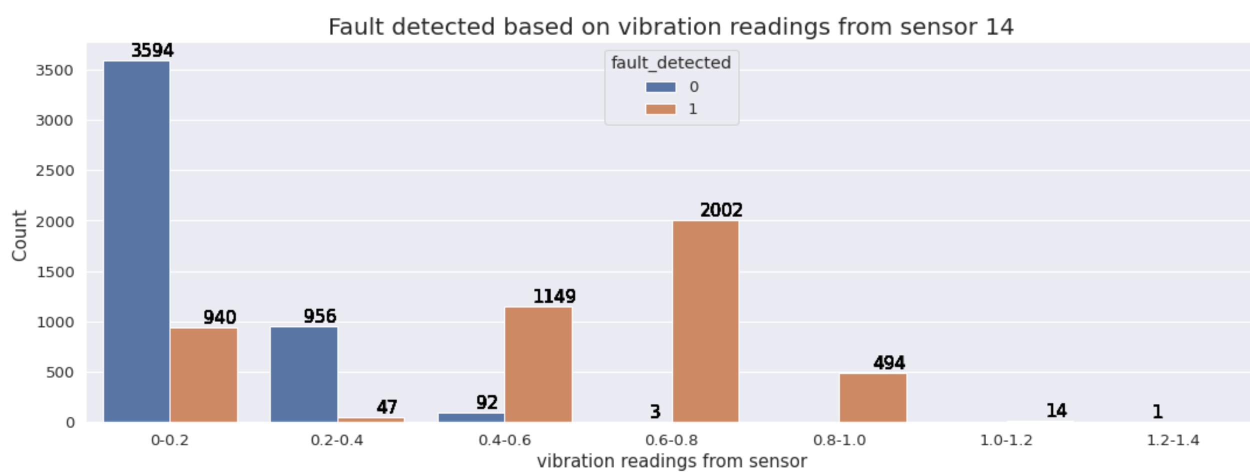



```
bins = [0, 0.2, 0.4, 0.6, 0.8, 1.0, 1.2, 1.4]
labels =['0-0.2', '0.2-0.4', '0.4-0.6', '0.6-0.8', '0.8-1.0', '1.0-1.2', '1.2-1.4']
df['binned_14'] = pd.cut(df['14'], bins=bins, labels =labels)
plt.figure(figsize=(16,7))
sns.countplot(x='binned_14',hue='fault_detected',  data = df)
plt.title(" Fault detected based on vibration readings from sensor 14", fontsize = 12)
plt.xlabel('vibration readings from sensor')
```

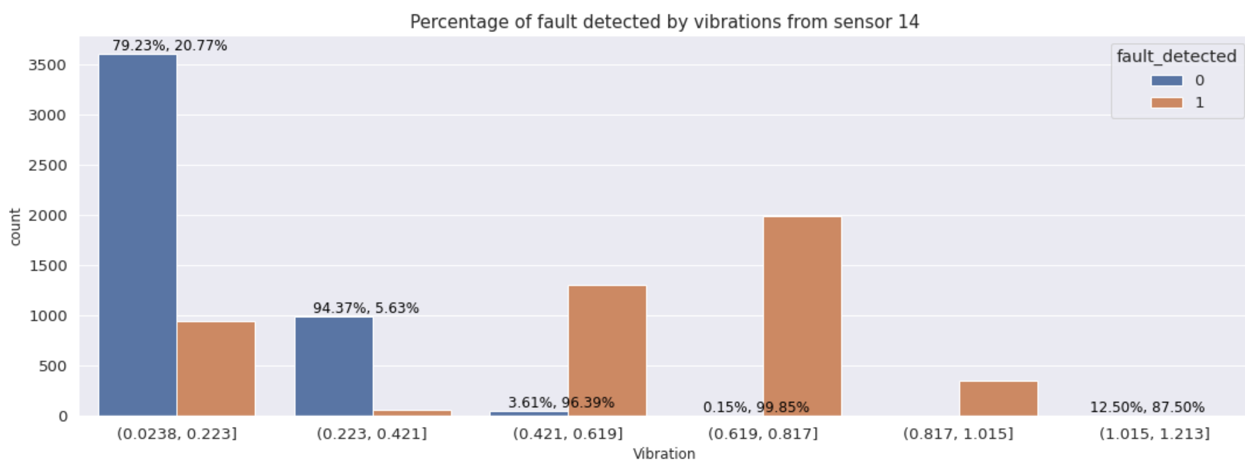
```
Out[28]: Text(0.5, 0, 'vibration readings from sensor')
```




```
plt.figure(figsize=(18,6))
sns.set(font_scale=1.2)
ax=sns.countplot(x='binned_14',hue='fault_detected',  data = df)
ax.set_title('Fault detected based on vibration readings from sensor 14' , fontsize = 20)
plt.xlabel('vibration readings from sensor', fontsize=15)
plt.ylabel('Count ', fontsize=15)
plt.xticks(rotation='horizontal')
for p in ax.patches:
    for p in ax.patches:
        ax.annotate(format(p.get_height(), '.0f'),
                    (p.get_x()+0.3, p.get_height()), ha='center', va='bottom', color='black', size=15)
```

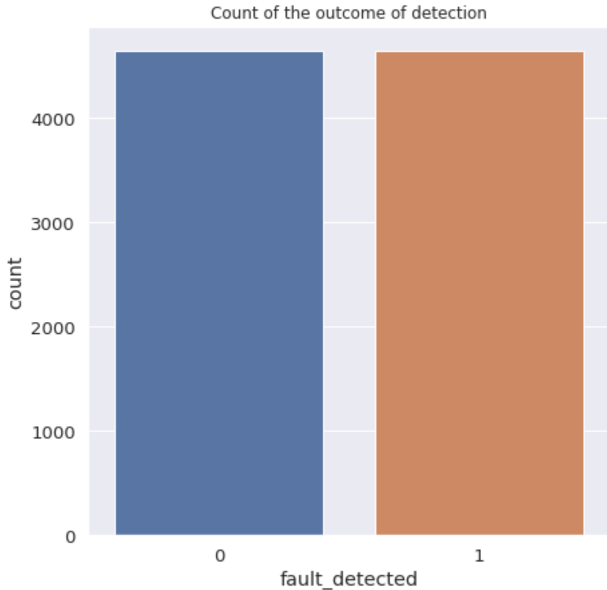


```
# Cut vibration readings inti bin and show the percenatge of fault detected within each bin
bin_sen_14 = pd.cut(df['14'], bins=6, ordered=True)
sen14_labels = [f'({interval.left}, {interval.right}]' for interval in bin_sen_14.cat.categories]
df['bins_sen_14'] = bin_sen_14.cat.rename_categories(sen14_labels )

# Create countplot
plt.figure(figsize=(18, 6))
sns.set(font_scale=1.2)
ax = sns.countplot(x='bins_sen_14',hue='fault_detected', data= df)
ax.set_title('Percentage of fault detected by vibrations from sensor 14', fontsize=15)
plt.xlabel('Vibration', fontsize=12)
plt.ylabel('count', fontsize=12)
plt.xticks(rotation='horizontal')

# Annotate plot with percentages
total_counts = df.groupby('bins_sen_14')['fault_detected'].count().reset_index(name='count')
fault_counts = df.groupby(['bins_sen_14', 'fault_detected']).size().reset_index(name='fault_count')

for p, label in zip(ax.patches, ax.get_xticklabels()):
    height = p.get_height()
    bin_label = label.get_text()
    bin_counts = fault_counts[fault_counts['bins_sen_14'] == bin_label]['fault_count']
    total_count = total_counts[total_counts['bins_sen_14'] == bin_label]['count'].iloc[0]
    percentages = [count / total_count * 100 for count in bin_counts]
    percentage_str = ', '.join([f'{percentage:.2f}%' for percentage in percentages])
    ax.annotate(percentage_str, (p.get_x() + p.get_width() / 2, height),
                ha='center', va='bottom', color='black', size=12,
                xytext=(28, 0), textcoords='offset points')

plt.show()
```




```
plt.figure(figsize=(7,7))
sns.countplot(x='fault_detected', data = df2)
plt.title('Count of the outcome of detection', fontsize = 12)
```

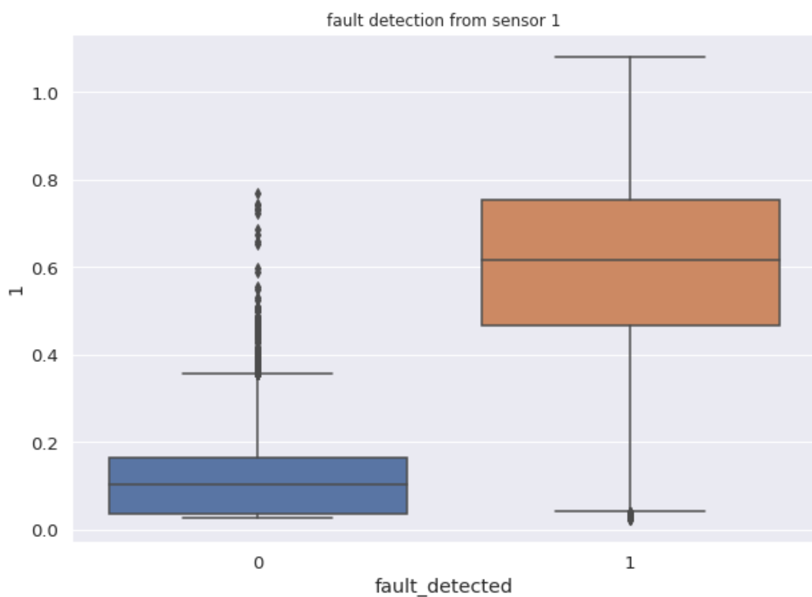
```
Out[31]: Text(0.5, 1.0, 'Count of the outcome of detection')
```




```
#To check if their are duplicated values
#set(FaultPandasFrame.duplicated())
```

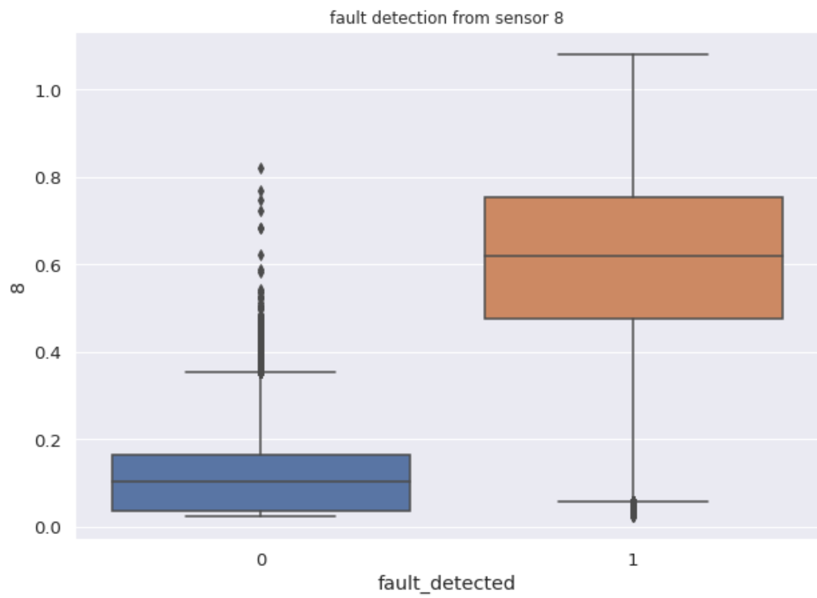
```
# A box plot to show the outcome of fault detection based on the readings for each sensor
# Readings from few sensors were checked: sensor 1, sensor 8 and sensor 14
plt.figure(figsize=(10,7))
sns.boxplot(y='1', x='fault_detected', data=df2)
plt.title('fault detection from sensor 1', fontsize = 12)
```

```
Out[33]: Text(0.5, 1.0, 'fault detection from sensor 1')
```



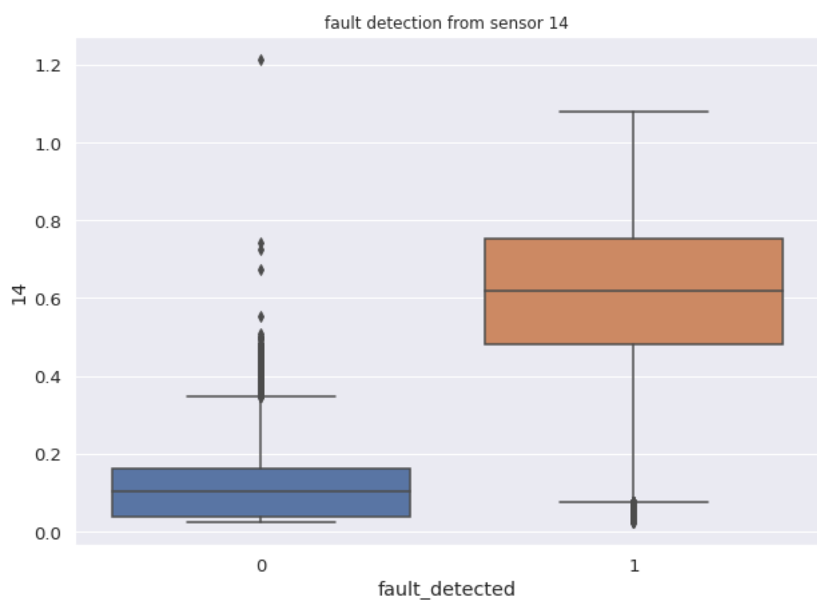

```
plt.figure(figsize=(10,7))
sns.boxplot(y='8', x='fault_detected', data=df2)
plt.title('fault detection from sensor 8', fontsize = 12)
```

```
Out[34]: Text(0.5, 1.0, 'fault detection from sensor 8')
```




```
plt.figure(figsize=(10,7))
sns.boxplot(y='14', x='fault_detected', data=df2)
plt.title('fault detection from sensor 14', fontsize = 12)
```

```
Out[35]: Text(0.5, 1.0, 'fault detection from sensor 14')
```




```
# Using the DataFrame created intiallly for further EDA
FaultsDF.printSchema()
```

```
root
 |-- 1: double (nullable = true)
 |-- 2: double (nullable = true)
 |-- 3: double (nullable = true)
 |-- 4: double (nullable = true)
 |-- 5: double (nullable = true)
 |-- 6: double (nullable = true)
 |-- 7: double (nullable = true)
 |-- 8: double (nullable = true)
 |-- 9: double (nullable = true)
 |-- 10: double (nullable = true)
 |-- 11: double (nullable = true)
```

```
 |-- 12: double (nullable = true)
 |-- 13: double (nullable = true)
 |-- 14: double (nullable = true)
 |-- 15: double (nullable = true)
 |-- 16: double (nullable = true)
 |-- 17: double (nullable = true)
 |-- 18: double (nullable = true)
 |-- 19: double (nullable = true)
```

```
FaultsDF.describe().display()
```

Table

| | summary | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| 1 | count | 9292 | 9292 | 9292 | 9292 | 9292 |
| 2 | mean | 0.34162330499354226 | 0.34263116121394677 | 0.3421213812957383 | 0.34213907124407966 | 0.342843440594058 |
| 3 | stddev | 0.28919489486260785 | 0.2890875372793958 | 0.28916422490616933 | 0.28916356333107296 | 0.288964655440387 |
| 4 | min | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 |
| 5 | max | 1.0809375 | 1.2134375 | 1.0809375 | 1.0809375 | 1.0809375 |

5 rows

```
# Let's also see the distribution of the result from the fault detected if the class is balance or not
# here the count funstion will be imported so that we can use it to count to outcome of each class of result
from pyspark.sql.functions import count as _count


# To check Class balance
FaultsDF.groupBy("fault_detected").agg(_count("*")).display()
```

Table

| | fault_detected | count(1) |
|---|---|---|
| 1 | 1 | 4646 |
| 2 | 0 | 4646 |

2 rows

```
# Importing some functions to help with further EDA
from pyspark.sql.functions import isnan, when, count, col



# Checking if there are missing values in each column
FaultsDF.select([_count(when(isnan(c), c)).alias(c) for c in FaultsDF.columns]).display()
```

Table

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

1 row

```
# Checking if there are missing values in each column
FaultsDF.select([_count(when(isnan(c), c)).alias(c) for c in FaultsDF.columns]).show()

+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+--------------+
|  1|  2|  3|  4|  5|  6|  7|  8|  9| 10| 11| 12| 13| 14| 15| 16| 17| 18| 19| 20|fault_detected|
+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+--------------+
|  0|  0|  0|  0|  0|  0|  0|  0|  0|  0|  0|  0|  0|  0|  0|  0|  0|  0|  0|  0|             0|
+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+--------------+
```

```
duplicates_ = FaultsDF.groupBy(FaultsDF.columns).count().filter(col("count") > 1)
print("Duplicates based on all columns:")
duplicates_.display()
```

```
Duplicates based on all columns:
```

Table

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.035625 | 0.0359375 | 0.0315625 | 0.035625 | 0.0365625 | 0.03625 | 0.040625 | 0.0409375 | 0.0421875 |
| 2 | 0.09875 | 0.09875 | 0.0978125 | 0.1028125 | 0.1003125 | 0.09625 | 0.1015625 | 0.10125 | 0.096875 |
| 3 | 0.0346875 | 0.036875 | 0.0353125 | 0.03875 | 0.0334375 | 0.0359375 | 0.0390625 | 0.0334375 | 0.03625 |
| 4 | 0.10625 | 0.10625 | 0.1021875 | 0.0971875 | 0.101875 | 0.1065625 | 0.1040625 | 0.101875 | 0.104375 |
| 5 | 0.1009375 | 0.1040625 | 0.101875 | 0.1078125 | 0.10875 | 0.1059375 | 0.1096875 | 0.111875 | 0.110625 |
| 6 | 0.035625 | 0.0334375 | 0.034375 | 0.03875 | 0.03875 | 0.0359375 | 0.03375 | 0.0346875 | 0.0375 |
| 7 | 0.4028125 | 0.3915625 | 0.3915625 | 0.384375 | 0.3859375 | 0.3871875 | 0.3975 | 0.398125 | 0.3896875 |

300 rows

```
# To confirm the number of rows and the distinct number of rows so we can identify if there is duplicated rows and see how many they are
row_count = FaultsDF.count()
distinct_count = FaultsDF.distinct().count()
print(row_count)
print(distinct_count)
```

```
9292
8968
```

```
print(row_count - distinct_count)
```

```
324
```

```
# To remove duplicated rows and keep only distinct rows

FaultsDF_drop = FaultsDF.distinct()
```

```
# To confirm that we now have 8968 rows since we have dropped the duplicated rows
FaultsDF_drop_count = FaultsDF_drop.distinct().count()
FaultsDF_drop_count
```

```
Out[47]: 8968
```

```
FaultsDF_drop.display()
```

Table

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.3634375 | 0.3665625 | 0.370625 | 0.369375 | 0.368125 | 0.3678125 | 0.3803125 | 0.37625 | 0.3809375 |
| 2 | 0.03875 | 0.03 | 0.0321875 | 0.0396875 | 0.0384375 | 0.031875 | 0.0384375 | 0.0384375 | 0.034375 |
| 3 | 0.1428125 | 0.1459375 | 0.1346875 | 0.1315625 | 0.130625 | 0.1346875 | 0.155 | 0.12625 | 0.1765625 |
| 4 | 0.033125 | 0.025 | 0.0303125 | 0.026875 | 0.033125 | 0.0328125 | 0.025 | 0.0290625 | 0.0328125 |
| 5 | 0.03375 | 0.0390625 | 0.03125 | 0.0390625 | 0.0384375 | 0.0390625 | 0.0325 | 0.03875 | 0.03625 |
| 6 | 0.0328125 | 0.0340625 | 0.031875 | 0.03625 | 0.0378125 | 0.038125 | 0.0359375 | 0.035625 | 0.034375 |
| 7 | 0.033125 | 0.0378125 | 0.0340625 | 0.03875 | 0.0325 | 0.0325 | 0.035 | 0.03375 | 0.03125 |

8,968 rows

```
FaultsDF_drop.describe().display()
```

Table

| | summary | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| 1 | count | 8968 | 8968 | 8968 | 8968 | 8968 |
| 2 | mean | 0.3487404870093662 | 0.3496980932203395 | 0.34913992807760935 | 0.3491733455062442 | 0.3500254028211428 |
| 3 | stddev | 0.29091106336065264 | 0.2907930998830016 | 0.29090468940487874 | 0.29089397507061654 | 0.2906356318628472 |
| 4 | min | 0.024375 | 0.024375 | 0.024375 | 0.024375 | 0.024375 |
| 5 | max | 1.0809375 | 1.2134375 | 1.0809375 | 1.0809375 | 1.0809375 |

5 rows

```
from pyspark.ml.feature import RFormula
Process = RFormula(formula= "fault_detected ~ .")
FaultDF = Process.fit(FaultsDF_drop).transform(FaultsDF_drop)
FaultDF.show(10)
```

```
2023/05/29 12:47:09 INFO mlflow.utils.autologging_utils: Created MLflow autologging run with ID '59347b1de50248eab25fecf8
5513b4a4', which will track hyperparameters, performance metrics, model artifacts, and lineage information for the curren
t pyspark.ml workflow
+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+
---------+---------+---------+---------+---------+---------+---------+---------+--------------+--------------------+-----
+
|        1|        2|        3|        4|        5|        6|        7|        8|        9|       10|       11|       12|
13|       14|       15|       16|       17|       18|       19|       20|fault_detected|            features|label|
+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+
---------+---------+---------+---------+---------+---------+---------+---------+--------------+--------------------+-----
+
|0.3634375|0.3665625| 0.370625| 0.369375| 0.368125|0.3678125|0.3803125|  0.37625|0.3809375|0.3815625|0.3928125|0.3834375|
0.36625| 0.379375|0.3684375|0.3728125|  0.36625| 0.379375|  0.37375| 0.376875|             0|[0.3634375,0.3665...|  0.0|
|  0.03875|     0.03|0.0321875|0.0396875|0.0384375| 0.031875|0.0384375|0.0384375| 0.034375|    0.035|0.0371875|0.0315625|
0.0328125| 0.031875|   0.0325|  0.03875|0.0365625|0.0378125|    0.035|0.0353125|             0|[0.03875,0.03,0.0...|  0.0
|
|0.1428125|0.1459375|0.1346875|0.1315625| 0.130625|0.1346875|    0.155|  0.12625|0.1765625|0.1403125|0.1434375| 0.139375|
0.139375|  0.13375|   0.1425|   0.1375|  0.12875| 0.131875| 0.130625|0.1353125|             0|[0.1428125,0.1459...|  0.0|
| 0.033125|    0.025|0.0303125| 0.026875| 0.033125|0.0328125|    0.025|0.0290625|0.0328125|0.0340625|     0.03|   0.0325|
0.0346875|  0.03125|  0.02875| 0.031875|0.0259375| 0.033125|     0.03| 0.026875|             0|[0.033125,0.025,0...|  0.0
|
```

```
#FaultDF.display(10)
```

```
# To split the data into training and testing data

(trainingDF, testingDF) = FaultDF.randomSplit([0.75, 0.25], seed =50)
```

```
# Training the model
# Using DecisionTreeClassifier
from pyspark.ml.classification import DecisionTreeClassifier
dt = DecisionTreeClassifier(labelCol="label", featuresCol="features")
model = dt.fit(trainingDF)
```

```
2023/05/29 12:47:11 INFO mlflow.utils.autologging_utils: Created MLflow autologging run with ID '4e74d60dd047452c9a348bba
df204f86', which will track hyperparameters, performance metrics, model artifacts, and lineage information for the curren
t pyspark.ml workflow
2023/05/29 12:48:25 WARNING mlflow.pyspark.ml: Model inputs contain unsupported Spark data types: [StructField('feature
s', VectorUDT(), True)]. Model signature is not logged.
2023/05/29 12:48:29 INFO mlflow.spark: Inferring pip requirements by reloading the logged model from the databricks artif
act repository, which can be time-consuming. To speed up, explicitly specify the conda_env or pip_requirements when calli
ng log_model().
2023/05/29 12:49:28 WARNING mlflow.utils.autologging_utils: MLflow autologging encountered a warning: "/databricks/pytho
n/lib/python3.9/site-packages/_distutils_hack/__init__.py:30: UserWarning: Setuptools is replacing distutils."
```

```
# To make predictions with the trained model
predictions = model.transform(testingDF)
predictions.show()
```

```
+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+
---------+---------+---------+---------+---------+---------+---------+---------+--------------+--------------------+-----
+--------------+--------------------+----------+
|        1|        2|        3|        4|        5|        6|        7|        8|        9|       10|       11|       12|
13|       14|       15|       16|       17|       18|       19|       20|fault_detected|            features|label| rawPr
ediction|         probability|prediction|
+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+
---------+---------+---------+---------+---------+---------+---------+---------+--------------+--------------------+-----
+--------------+--------------------+----------+
|  0.02625| 0.025625|0.0290625|0.0265625|0.0353125|0.0259375|0.0328125|0.0340625|  0.03375|0.0309375|0.0309375| 0.034375|
0.030625| 0.029375| 0.029375| 0.026875| 0.030625|0.0284375|  0.03125|0.0271875|             0|[0.02625,0.025625...|  0.0|
[3151.0,149.0]|[0.95484848484848...|       0.0|
|0.0265625|0.0284375|  0.02625|   0.0325|0.0296875|0.0353125|0.0328125|0.0265625|  0.03125|0.0328125| 0.029375|0.0284375|
0.0334375|0.0321875|0.0296875|   0.0325|0.0284375|0.0259375|  0.03125|  0.02875|             1|[0.0265625,0.0284...|  1.0
|[3151.0,149.0]|[0.95484848484848...|       0.0|
| 0.026875|0.0346875|  0.03125|0.0303125|0.0315625|  0.02875|0.0278125| 0.034375|   0.0325|   0.0375| 0.030625|  0.03625|
0.0334375|0.0346875|0.0284375|0.0290625|0.0296875| 0.031875|0.0315625|0.0315625|             0|[0.026875,0.03468...|  0.0
|[3151.0,149.0]|[0.95484848484848...|       0.0|
|0.0278125|   0.0275|  0.02875|    0.035| 0.029375|0.0284375| 0.028125|0.0340625| 0.030625|0.0315625|0.0265625|0.0253125|
0.0259375|0.0284375|0.0296875|0.0340625|0.0328125|0.0328125|   0.0325|    0.025|             1|[0.0278125,0.0275...|  1.0
|[3151.0,149.0]|[0.95484848484848...|       0.0|
```

```
predictions.show(2)
```

```
+---------+---------+---------+---------+---------+---------+---------+---------+---------+-------+---------+---------+---------+--
-------+---------+---------+--------+---------+---------+-------+---------+--------------+--------------------+-----+----
----------+--------------------+----------+
|        1|        2|        3|        4|        5|        6|        7|        8|      9|       10|       11|       12|
13|       14|       15|       16|       17|       18|     19|       20|fault_detected|            features|label| rawPredi
ction|         probability|prediction|
+---------+---------+---------+---------+---------+---------+---------+---------+---------+-------+---------+---------+---------+--
-------+---------+---------+--------+---------+---------+-------+---------+--------------+--------------------+-----+----
----------+--------------------+----------+
|  0.02625| 0.025625|0.0290625|0.0265625|0.0353125|0.0259375|0.0328125|0.0340625|0.03375|0.0309375|0.0309375| 0.034375|
0.030625| 0.029375| 0.029375|0.026875| 0.030625|0.0284375|0.03125|0.0271875|             0|[0.02625,0.025625...|  0.0|[31
51.0,149.0]|[0.95484848484848...|       0.0|
|0.0265625|0.0284375|  0.02625|   0.0325|0.0296875|0.0353125|0.0328125|0.0265625|0.03125|0.0328125| 0.029375|0.0284375|0.
0334375|0.0321875|0.0296875|  0.0325|0.0284375|0.0259375|0.03125|  0.02875|             1|[0.0265625,0.0284...|  1.0|[315
1.0,149.0]|[0.95484848484848...|       0.0|
+---------+---------+---------+---------+---------+---------+---------+---------+---------+-------+---------+---------+---------+--
-------+---------+---------+--------+---------+---------+-------+---------+--------------+--------------------+-----+----
----------+--------------------+----------+
only showing top 2 rows
```

```
predictions.display()
```

Table

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.02625 | 0.025625 | 0.0290625 | 0.0265625 | 0.0353125 | 0.0259375 | 0.0328125 | 0.0340625 | 0.03375 |
| 2 | 0.0265625 | 0.0284375 | 0.02625 | 0.0325 | 0.0296875 | 0.0353125 | 0.0328125 | 0.0265625 | 0.03125 |
| 3 | 0.026875 | 0.0346875 | 0.03125 | 0.0303125 | 0.0315625 | 0.02875 | 0.0278125 | 0.034375 | 0.0325 |
| 4 | 0.0278125 | 0.0275 | 0.02875 | 0.035 | 0.029375 | 0.0284375 | 0.028125 | 0.0340625 | 0.030625 |
| 5 | 0.0278125 | 0.0284375 | 0.0271875 | 0.0284375 | 0.0309375 | 0.0309375 | 0.02875 | 0.0340625 | 0.0296875 |
| 6 | 0.0278125 | 0.03 | 0.0284375 | 0.029375 | 0.02875 | 0.03125 | 0.0325 | 0.0290625 | 0.02625 |
| 7 | 0.0278125 | 0.038125 | 0.036875 | 0.1553125 | 0.1696875 | 0.1809375 | 0.189375 | 0.176875 | 0.1646875 |

2,255 rows

```
# To evaluate the accuracy of predictiosn made by the model, we can use the multiclass classificationevaluator
from pyspark.ml.evaluation import  MulticlassClassificationEvaluator
evaluator = MulticlassClassificationEvaluator(labelCol="label", predictionCol="prediction", metricName="accuracy")
accuracy = evaluator.evaluate(predictions)
print("Accuracy score: %g " %(accuracy))
```

```
Accuracy score: 0.968071
```

```
# Using MLflow to track experiment
```

```
from pyspark.ml.tuning import ParamGridBuilder, TrainValidationSplit
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.ml.classification import DecisionTreeClassifier
from pyspark.sql.functions import col


# start an MLflow run and giving it a name for easy identification in the logs
with mlflow.start_run(run_name="decision_tree_classification") as run:

    # create an instance of  decision tree classifier
    dt = DecisionTreeClassifier(featuresCol="features", labelCol="label")

    # creating a parameter grid of  different values
    paramGrid = (ParamGridBuilder()
                 .addGrid(dt.maxDepth, [7,9 ])
                 .addGrid(dt.maxBins, [12,32])
                 .addGrid(dt.impurity, ['gini', 'entropy'])
                 .build())

    # creating a TrainValidationSplit object
    tvs = TrainValidationSplit(estimator=dt,
                               estimatorParamMaps=paramGrid,
                               evaluator=MulticlassClassificationEvaluator()
                              )
    # fit the model
    model = tvs.fit(trainingDF)

    # retrieving a dictionary of the hyperparameters and values of the best model
    best_parameters = model.bestModel.extractParamMap()
    # log the best model parameters
    for param, value in best_parameters.items():

        with mlflow.start_run(nested=True):
            mlflow.log_param("depth", 7)
        with mlflow.start_run(nested=True):
            mlflow.log_param("depth", 9)

    # The best trained  model
    best_model_1=model.bestModel

    # using the best model on the testing data and evaluating the accuracy

    evaluator = MulticlassClassificationEvaluator(labelCol="label",
                                                  predictionCol="prediction",
                                                  metricName="accuracy")
    accuracy_1 = evaluator.evaluate(best_model_1.transform(testingDF))

    # log the accuracy of the best model
    mlflow.log_metric("accuracy", accuracy_1)

    # end the MLflow run
    mlflow.end_run()
```

```
2023/05/29 13:10:07 INFO mlflow.spark: Inferring pip requirements by reloading the logged model from the databricks artif
act repository, which can be time-consuming. To speed up, explicitly specify the conda_env or pip_requirements when calli
ng log_model().
2023/05/29 13:11:19 INFO mlflow.spark: Inferring pip requirements by reloading the logged model from the databricks artif
act repository, which can be time-consuming. To speed up, explicitly specify the conda_env or pip_requirements when calli
ng log_model().
```

```
print(accuracy_1)
```

```
0.9818181818181818
```

```
# To get the best parameters
print("Tuned parameters for the best model: ")
print("MaxDepth: %g" %best_model_1.getMaxDepth())
print("MaxBins: %g" %best_model_1.getMaxBins())
print("Impurity: %s" %best_model_1.getImpurity())
```

```
Tuned parameters for the best model:
MaxDepth: 9
MaxBins: 32
Impurity: entropy
```

```
# RandomForest Classifier
```

```
# Splitting data for  RandomForest classification models
(trainingDF2, testingDF2) = FaultDF.randomSplit([0.75, 0.25], seed =20)
```

```
from pyspark.ml.classification import RandomForestClassifier
```

```
# creating an instance of  random forest classifier and fitting it into the training data
rf = RandomForestClassifier(labelCol="label", featuresCol="features")
model2=rf.fit(trainingDF2)
```

```
2023/05/29 13:12:35 INFO mlflow.utils.autologging_utils: Created MLflow autologging run with ID '35931319b9124ed586990c55
76539974', which will track hyperparameters, performance metrics, model artifacts, and lineage information for the curren
t pyspark.ml workflow
2023/05/29 13:14:38 INFO mlflow.spark: Inferring pip requirements by reloading the logged model from the databricks artif
act repository, which can be time-consuming. To speed up, explicitly specify the conda_env or pip_requirements when calli
ng log_model().
```

```
# Making predictions with the Random Forest classifer model
predictions2 = model2.transform(testingDF2)
predictions2.show()
```

```
+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+
---------+---------+---------+---------+---------+---------+---------+---------+--------------+--------------------+-----
+--------------------+--------------------+----------+
|        1|        2|        3|        4|        5|        6|        7|        8|        9|       10|       11|       12|
13|       14|       15|       16|       17|       18|       19|       20|fault_detected|            features|label|
rawPrediction|         probability|prediction|
+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+
---------+---------+---------+---------+---------+---------+---------+---------+--------------+--------------------+-----
+--------------------+--------------------+----------+
|0.0253125|0.0259375|0.0284375|0.0296875|0.0340625|0.0328125|0.0328125|   0.0325|    0.025|0.0334375| 0.035625|  0.02875|
0.0334375|     0.03| 0.030625| 0.026875|  0.02875|0.0359375|    0.035|  0.03875|             1|[0.0253125,0.0259...|  1.0
|[19.0147178961624...|[0.95073589480812...|       0.0|
|  0.02625|0.0334375|0.0271875|   0.0275|  0.02625| 0.034375|0.0321875| 0.031875| 0.031875|0.0346875|0.0340625|0.0303125|
0.03375|  0.03125|0.0290625|   0.0325|0.0328125| 0.029375|0.0253125| 0.039375|             1|[0.02625,0.033437...|  1.0|
[19.0147178961624...|[0.95073589480812...|       0.0|
```

```
|0.0265625|0.0296875|0.0278125|   0.0275|  0.02875|    0.035| 0.029375|0.0284375| 0.028125|0.0340625| 0.030625|0.0315625|
0.0265625|0.0253125|0.0259375|0.0284375|0.0296875|0.0340625|0.0328125|0.0328125|            1|[0.0265625,0.0296...|  1.0
|[19.0147178961624...|[0.95073589480812...|       0.0|
|0.0265625|0.0296875|0.0278125|0.0284375|0.0271875|0.0284375|0.0309375|0.0309375|  0.02875|0.0340625|0.0296875|  0.03125|
0.0359375| 0.671875|0.0640625|     0.07|0.0603125|0.0778125|0.0984375|  0.07875|            1|[0.0265625,0.0296...|  1.0
```

```
#predictions2.display()
```

```
# Evaluating accuracy of the randomForestClassifier without hyperparameter tuning
evaluator = MulticlassClassificationEvaluator(labelCol="label", predictionCol="prediction", metricName="accuracy")
accuracyRF = evaluator.evaluate(predictions2)
print("Accuracy score: ", accuracyRF)
```

```
Accuracy score:  0.9777979157227005
```

```
# Random Forest classifier model using several hyperparameters and getting the best model
with mlflow.start_run(run_name="random_forest_classification") as run:

    # create an instance of Random Forest classifier
    rf = RandomForestClassifier(labelCol="label", featuresCol="features")

    # parameter grid with different values
    RFParamGrid = (ParamGridBuilder()
                 .addGrid(rf.numTrees, [10,15 ])
                 .addGrid(rf.maxDepth, [9,13])
                 .build())

    # create a TrainValidationSplit object
    RFtvs = TrainValidationSplit(estimator=rf,
                               estimatorParamMaps=RFParamGrid,
                               evaluator=MulticlassClassificationEvaluator()
                            )

    # fit the model and retrieve the best model
    model = RFtvs.fit(trainingDF2)

    # retrieving a dictionary of hyperparameters and values of the best model
    best_parameters = model.bestModel.extractParamMap()
    # log the best model parameters
    for param, value in best_parameters.items():

        with mlflow.start_run(nested=True):
            mlflow.log_param("depth", 9)
        with mlflow.start_run(nested=True):
            mlflow.log_param("depth", 13)


     # The best trained  model
    best_model_2 =model.bestModel

    # using the best model on the testing data

    evaluator = MulticlassClassificationEvaluator(labelCol="label",
                                              predictionCol="prediction",
                                              metricName="accuracy")
    accuracy_2 = evaluator.evaluate(best_model_2.transform(testingDF2))

    # log the accuracy of the best model
    mlflow.log_metric("accuracy", accuracy_2)

    # end the MLflow run
    mlflow.end_run()
```

```
2023/05/29 13:41:23 INFO mlflow.spark: Inferring pip requirements by reloading the logged model from the databricks artif
act repository, which can be time-consuming. To speed up, explicitly specify the conda_env or pip_requirements when calli
ng log_model().
```

```
2023/05/29 13:42:36 INFO mlflow.spark: Inferring pip requirements by reloading the logged model from the databricks artif
act repository, which can be time-consuming. To speed up, explicitly specify the conda_env or pip_requirements when calli
ng log_model().
```

```
# Accuracy using the best model
print(accuracy_2)
```

```
0.9841413683733575
```

```
# Parameters of best model from Random forest classifier
print("Tuned parameters for the best model: ")
print("MaxDepth: ", best_model_2.getMaxDepth())
print("numTrees: ", best_model_2.getNumTrees)
```

```
Tuned parameters for the best model:
MaxDepth:  9
numTrees:  15
```