Wafer_Fault_Detection

June 17, 2023

# 1 Problem Statement: Wafer Fault Detection

## 1.1 Description:

- **In electronics, a** wafer** (also called a slice or substrate) is a thin slice of semiconductor, such as a crystalline silicon (c-Si), used for the fabrication of integrated circuits and, in photovoltaics, to manufacture solar cells. The wafer serves as the substrate(serves as foundation for contruction of other components) for microelectronic devices built in and upon the wafer.**
- **It undergoes many microfabrication processes, such as doping, ion implantation, etching, thin-film deposition of various materials, and photolithographic patterning. Finally, the individual microcircuits are separated by wafer dicing and packaged as an integrated circuit.**
- **Wafers are predominantly used to manufacture solar cells and are located at remote locations in bulk and they themselves consist of few hundreds of sensors. Wafers are fundamental of photovoltaic power generation, and production thereof requires high technology. Photovoltaic power generation system converts sunlight energy directly to electrical energy.**
- **The motto behind figuring out the faulty wafers is to obliterate the need of having manual man-power doing the same. And make no mistake when we're saying this, even when they suspect a certain wafer to be faulty, they had to open the wafer from the scratch and deal with the issue, and by doing so all the wafers in the vicinity had to be stopped disrupting the whole process and stuff anf this is when that certain wafer was indeed faulty, however, when their suspicion came outta be false negative, then we can only imagine the waste of time, man-power and ofcourse, cost incurred.**

# 2 1. Importing Libraries

[ ]:
```
import pandas as pd
import numpy as np

from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.impute import KNNImputer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import RobustScaler
```

```
from sklearn.cluster import KMeans
#from kneed import KneeLocator
from typing import Tuple
from dataclasses import dataclass
from imblearn.combine import SMOTETomek
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import roc_auc_score

import warnings
warnings.filterwarnings('ignore')

import seaborn as sns
import matplotlib.pyplot as plt
```

# 3 2. The Datasets

# 4 2.1 Reading Datasets

[ ]:
```
wafers=pd.read_csv('/home/blackheart/Documents/DATA SCIENCE/PROJECT/
↪Wafer_Fault_Detection/notebooks/wafer_23012020_041211.csv')
wafers.head()
```

[ ]:
```
  Unnamed: 0  Sensor-1  Sensor-2   Sensor-3   Sensor-4  Sensor-5  Sensor-6
0  Wafer-801   2968.33   2476.58  2216.7333  1748.0885    1.1127     100.0  \
1  Wafer-802   2961.04   2506.43  2170.0666  1364.5157    1.5447     100.0
2  Wafer-803   3072.03   2500.68  2205.7445  1363.1048    1.0518     100.0
3  Wafer-804   3021.83   2419.83  2205.7445  1363.1048    1.0518     100.0
4  Wafer-805   3006.95   2435.34  2189.8111  1084.6502    1.1993     100.0

   Sensor-7  Sensor-8  Sensor-9  …  Sensor-582  Sensor-583  Sensor-584
0   97.5822    0.1242    1.5300  …         NaN      0.5004      0.0120  \
1   96.7700    0.1230    1.3953  …         NaN      0.4994      0.0115
2  101.8644    0.1220    1.3896  …         NaN      0.4987      0.0118
3  101.8644    0.1220    1.4108  …         NaN      0.4934      0.0123
4  104.8856    0.1234    1.5094  …         NaN      0.4987      0.0145

   Sensor-585  Sensor-586  Sensor-587  Sensor-588  Sensor-589  Sensor-590
0      0.0033      2.4069      0.0545      0.0184      0.0055     33.7876  \
1      0.0031      2.3020      0.0545      0.0184      0.0055     33.7876
2      0.0036      2.3719      0.0545      0.0184      0.0055     33.7876
3      0.0040      2.4923      0.0545      0.0184      0.0055     33.7876
4      0.0041      2.8991      0.0545      0.0184      0.0055     33.7876
```

```
   Good/Bad
0        -1
1         1
2        -1
3        -1
4        -1

[5 rows x 592 columns]
```

### 4.1 Summary Of Datasets:

- **The dataset contains information about 1000 wafers, each of which has been inspected for defects. The features of each wafer include its X and Y coordinates, the type of defect (crack, pit, or scratch), and the size of the defect. The labels indicate whether the wafer is faulty or not faulty.**
- **The dataset can be used to train a machine learning model to predict whether a wafer is faulty based on its features. This could be used to improve the yield of semiconductor manufacturing processes.**

Here are some additional details about the dataset:

- The data was collected from a semiconductor manufacturing plant.
- The data was collected using a microscope.
- The data was labeled by a human expert.
- The data is clean and well-formatted.
- The data is representative of the real-world problem of wafer fault prediction.

### 4.2 2.2 Test Datasets

- *Creating test datasets for testing purpose*

[ ]:
```
wafers.drop(columns=['Unnamed: 0']).iloc[:100].to_csv('test.csv',index=False)
```

## 5 3. Data Exploration

[ ]:
```
wafers.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Columns: 592 entries, Unnamed: 0 to Good/Bad
dtypes: float64(494), int64(97), object(1)
memory usage: 462.6+ KB
```

[ ]:
```
wafers.describe()
```

[ ]:
```
         Sensor-1    Sensor-2    Sensor-3    Sensor-4   Sensor-5
count   99.000000  100.000000   97.000000   97.000000  97.000000  \
```

```
mean   3017.301212  2487.180300  2202.168281  1484.362181   1.180367
std      71.819707    66.954212    30.350606   460.985871   0.349654
min    2825.670000  2254.990000  2114.666700   978.783200   0.753100
25%    2973.040000  2446.595000  2189.966700  1111.543600   0.837300
50%    3004.390000  2493.890000  2200.988900  1244.289900   1.156900
75%    3070.385000  2527.525000  2213.211100  1963.801600   1.383000
max    3221.210000  2664.520000  2315.266700  2363.641200   2.207300

       Sensor-6    Sensor-7   Sensor-8    Sensor-9   Sensor-10  …
count      97.0   97.000000  97.000000  100.000000  100.000000  …  \
mean      100.0   97.449088   0.122195    1.461516    0.000243  …
std         0.0    5.553324   0.002006    0.071300    0.010610  …
min       100.0   83.423300   0.116000    1.317900   -0.027900  …
25%       100.0   95.108900   0.120800    1.407375   -0.006925  …
50%       100.0   99.513300   0.122200    1.453700    0.001000  …
75%       100.0  101.457800   0.123400    1.507425    0.008125  …
max       100.0  107.152200   0.126200    1.641100    0.025000  …

       Sensor-582  Sensor-583  Sensor-584  Sensor-585  Sensor-586  Sensor-587
count   34.000000  100.000000  100.000000  100.000000  100.000000  100.000000  \
mean    74.331709    0.499390    0.013615    0.003549    2.727297    0.023510
std     41.857728    0.003431    0.004344    0.000873    0.875848    0.011991
min     20.309100    0.492500    0.007600    0.002100    1.515200    0.009900
25%     47.356000    0.497300    0.011300    0.003075    2.270425    0.013400
50%     65.127550    0.499400    0.012750    0.003400    2.546400    0.021800
75%     99.419050    0.501525    0.014700    0.003825    2.953750    0.028025
max    223.101800    0.508700    0.043700    0.008900    8.816000    0.054500

       Sensor-588  Sensor-589  Sensor-590    Good/Bad
count  100.000000  100.000000  100.000000  100.000000
mean     0.014875    0.004685   77.430241   -0.880000
std      0.007557    0.002527   55.106166    0.477367
min      0.004800    0.001700   20.309100   -1.000000
25%      0.009475    0.002700   33.787600   -1.000000
50%      0.013900    0.003850   62.059500   -1.000000
75%      0.019200    0.005900  104.303400   -1.000000
max      0.040100    0.015000  223.101800    1.000000

[8 rows x 591 columns]
```

[ ]:
```python
wafers.columns.unique()
```

[ ]:
```
Index(['Unnamed: 0', 'Sensor-1', 'Sensor-2', 'Sensor-3', 'Sensor-4',
       'Sensor-5', 'Sensor-6', 'Sensor-7', 'Sensor-8', 'Sensor-9',
       …
       'Sensor-582', 'Sensor-583', 'Sensor-584', 'Sensor-585', 'Sensor-586',
       'Sensor-587', 'Sensor-588', 'Sensor-589', 'Sensor-590', 'Good/Bad'],
```

```
      dtype='object', length=592)
```

- **Replacing Unnamed: 0 to Wafer**

[ ]:
```python
wafers.rename(columns={'Unnamed: 0': 'Wafer'},inplace=True)
```

[ ]:
```python
wafers.head(2)
```

[ ]:
```
        Wafer  Sensor-1  Sensor-2   Sensor-3   Sensor-4  Sensor-5  Sensor-6  
0  Wafer-801   2968.33   2476.58  2216.7333  1748.0885    1.1127     100.0   \
1  Wafer-802   2961.04   2506.43  2170.0666  1364.5157    1.5447     100.0

   Sensor-7  Sensor-8  Sensor-9  …  Sensor-582  Sensor-583  Sensor-584  
0   97.5822    0.1242    1.5300  …         NaN      0.5004      0.0120  \
1   96.7700    0.1230    1.3953  …         NaN      0.4994      0.0115

   Sensor-585  Sensor-586  Sensor-587  Sensor-588  Sensor-589  Sensor-590  
0      0.0033      2.4069      0.0545      0.0184      0.0055     33.7876   \
1      0.0031      2.3020      0.0545      0.0184      0.0055     33.7876

   Good/Bad
0        -1
1         1

[2 rows x 592 columns]
```

- **Let's see how many wafers is good and how many bad**

[ ]:
```python
wafers['Good/Bad'].value_counts()
```

[ ]:
```
Good/Bad
-1    94
 1     6
Name: count, dtype: int64
```

- This data is havily imbalanced datasets so we have to balanced it.

### 5.1 3.1 Handling Missing Value

Firstly, we'll check the missing data in the target feature and drop those records. **As if we already know a value of target feature then there's no need for a ML algorithm, damn right?** Therefore, the best way to deal with missing target entries is to delete them. For other missing features, we can definitely use impute strategies.

[ ]:
```python
wafers['Good/Bad'].isna().sum()
```

[ ]:
```
0
```

[ ]:
```python
wafers.isna().sum()
```

```
[ ]: Wafer          0
     Sensor-1       1
     Sensor-2       0
     Sensor-3       3
     Sensor-4       3
                   ..
     Sensor-587     0
     Sensor-588     0
     Sensor-589     0
     Sensor-590     0
     Good/Bad       0
     Length: 592, dtype: int64
```

```
[ ]: wafers.isna().sum().sum()
```

```
[ ]: 2306
```

```
[ ]: ## Check missing vals in dependent feature variables

     wafers.isna().sum().sum() / (wafers.shape[0] * (wafers.shape[1] - 1))
```

```
[ ]: 0.03901861252115059
```

- **Almost 4% missing data**

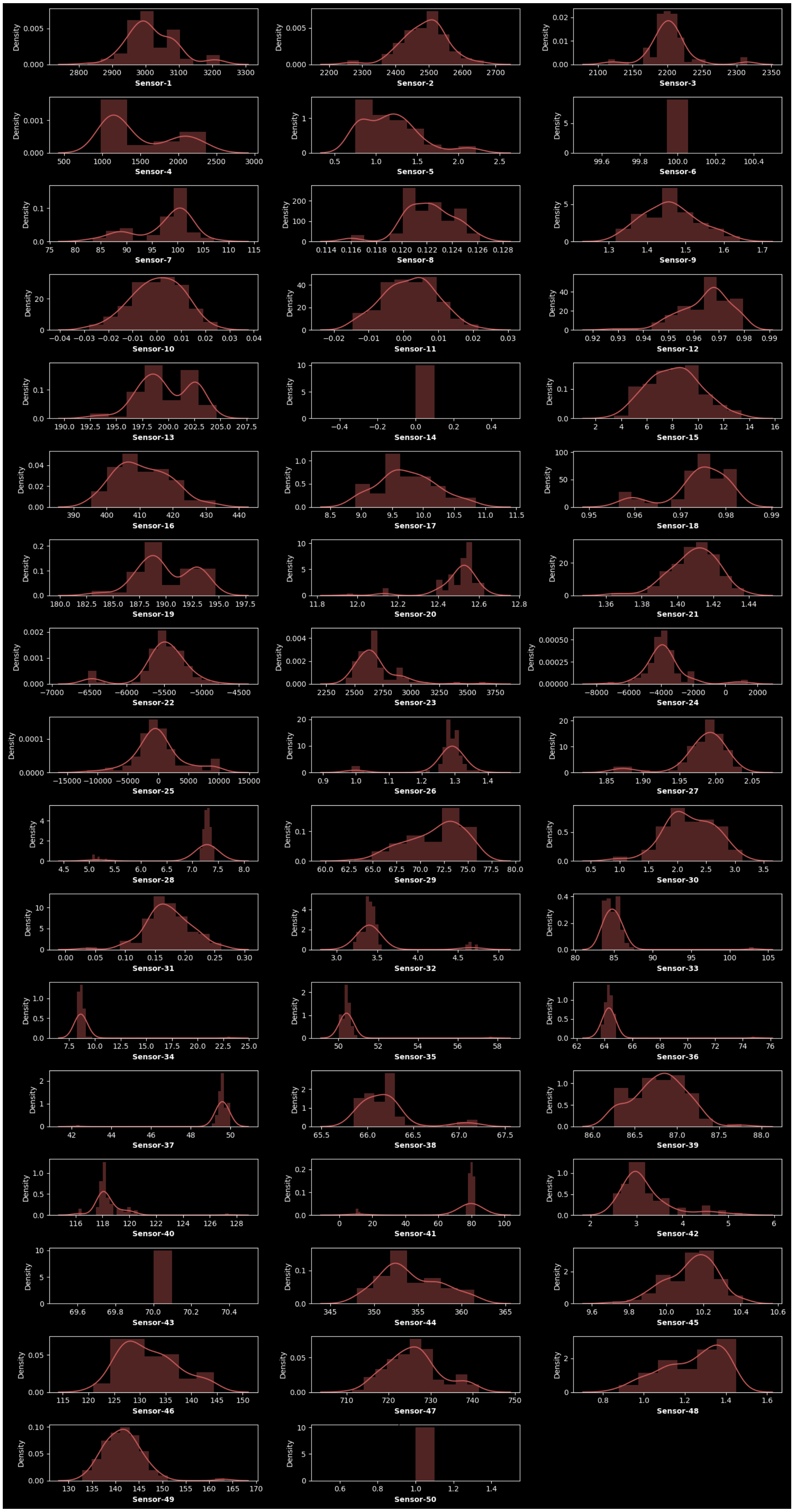
# 6 3. Data Visualization

```
[ ]: plt.style.use('dark_background')
```

```
[ ]: # let's have a look at the distribution first 50 sensors of Wafers

     plt.figure(figsize=(15, 100))

     for i, col in enumerate(wafers.columns[1:51]):
         plt.subplot(60, 3, i+1)
         sns.distplot(x=wafers[col], color='indianred')
         plt.xlabel(col, weight='bold')
         plt.tight_layout()
```


Density
Sensor-1
Sensor-2
Sensor-3
Sensor-4
Sensor-5
Sensor-6
Sensor-7
Sensor-8
Sensor-9
Sensor-10
Sensor-11
Sensor-12
Sensor-13
Sensor-14
Sensor-15
Sensor-16
Sensor-17
Sensor-18
Sensor-19
Sensor-20
Sensor-21
Sensor-22
Sensor-23
Sensor-24
Sensor-25
Sensor-26
Sensor-27
Sensor-28
Sensor-29
Sensor-30
Sensor-31
Sensor-32
Sensor-33
Sensor-34
Sensor-35
Sensor-36
Sensor-37
Sensor-38
Sensor-39
Sensor-40
Sensor-41
Sensor-42
Sensor-43
Sensor-44
Sensor-45
Sensor-46
Sensor-47
Sensor-48
Sensor-49
Sensor-50

[ ]:

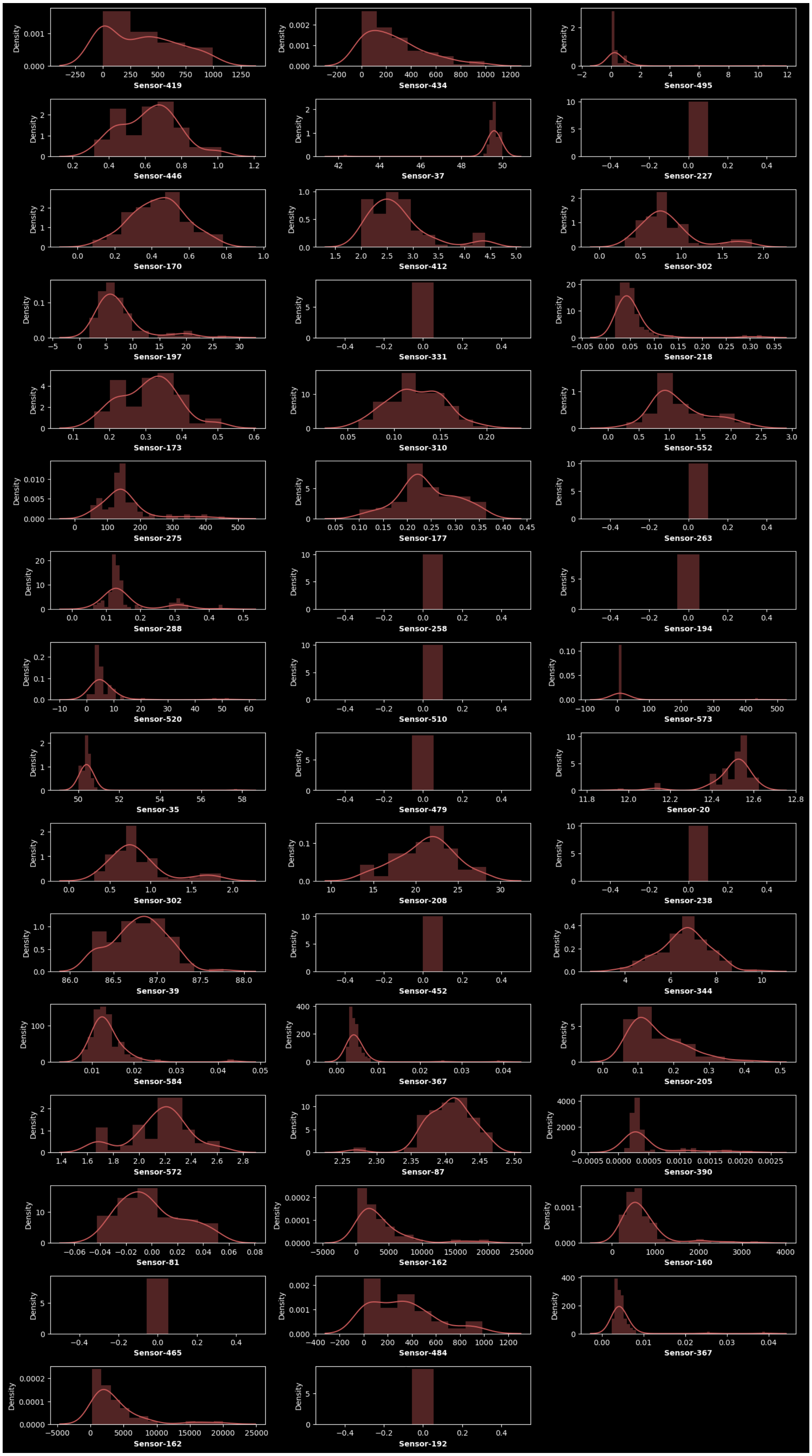
```python
# Select 50 random sensors

random_50_sensors_idx = []
for i in range(50):
    if i not in random_50_sensors_idx:
        random_50_sensors_idx.append(np.random.randint(1, 591))


# let's now, have a look at the distribution of random 50 sensors

plt.figure(figsize=(15, 100))

for i, col in enumerate(wafers.columns[random_50_sensors_idx]):
    plt.subplot(60, 3, i+1)
    sns.distplot(x=wafers[col], color='indianred')
    plt.xlabel(col, weight='bold')
    plt.tight_layout()
```



Sensor-419
Sensor-434
Sensor-495
Sensor-446
Sensor-37
Sensor-227
Sensor-170
Sensor-412
Sensor-302
Sensor-197
Sensor-331
Sensor-218
Sensor-173
Sensor-310
Sensor-552
Sensor-275
Sensor-177
Sensor-263
Sensor-288
Sensor-258
Sensor-194
Sensor-520
Sensor-510
Sensor-573
Sensor-35
Sensor-479
Sensor-20
Sensor-302
Sensor-208
Sensor-238
Sensor-39
Sensor-452
Sensor-344
Sensor-584
Sensor-367
Sensor-205
Sensor-572
Sensor-87
Sensor-390
Sensor-81
Sensor-162
Sensor-160
Sensor-465
Sensor-484
Sensor-367
Sensor-162
Sensor-192

### 6.0.1 Insight:

Pretty good amount of them (either first 50 or random 50) either are constant (have 0 standard deviation) or have left skewness and right skewness. It ain't possible to analyze each feature and deal with its outliers individually, thus we oughta depend upon the scaling.

For the **features with 0 standard deviation**, we can straight away drop them and for others that do have outliers, we gotta go ahead with the `Robust Scaling`.

- **Now we are going to drop whose columns have 0 standard deviation**

[ ]:
```
def get_cols_with_zero_std_dev(df: pd.DataFrame):
    """
    Returns a list of columns names who are having zero standard deviation.
    """
    cols_to_drop = []
    num_cols = [col for col in df.columns if df[col].dtype != 'O']  # numerical␣
 ↪cols only
    for col in num_cols:
        if df[col].std() == 0:
            cols_to_drop.append(col)
    return cols_to_drop
```

[ ]:
```
## Columns w 0 Standard Deviation

cols_to_drop_2 = get_cols_with_zero_std_dev(df=wafers)
cols_to_drop_2.append("Wafer")
cols_to_drop_2
```

[ ]:
```
['Sensor-6',
 'Sensor-14',
 'Sensor-43',
 'Sensor-50',
 'Sensor-53',
 'Sensor-70',
 'Sensor-75',
 'Sensor-98',
 'Sensor-142',
 'Sensor-150',
 'Sensor-179',
 'Sensor-180',
 'Sensor-187',
 'Sensor-190',
 'Sensor-191',
 'Sensor-192',
 'Sensor-193',
```

```
'Sensor-194',
'Sensor-195',
'Sensor-207',
'Sensor-210',
'Sensor-227',
'Sensor-230',
'Sensor-231',
'Sensor-232',
'Sensor-233',
'Sensor-234',
'Sensor-235',
'Sensor-236',
'Sensor-237',
'Sensor-238',
'Sensor-241',
'Sensor-242',
'Sensor-243',
'Sensor-244',
'Sensor-257',
'Sensor-258',
'Sensor-259',
'Sensor-260',
'Sensor-261',
'Sensor-262',
'Sensor-263',
'Sensor-264',
'Sensor-265',
'Sensor-266',
'Sensor-267',
'Sensor-277',
'Sensor-285',
'Sensor-314',
'Sensor-315',
'Sensor-316',
'Sensor-323',
'Sensor-326',
'Sensor-327',
'Sensor-328',
'Sensor-329',
'Sensor-330',
'Sensor-331',
'Sensor-343',
'Sensor-348',
'Sensor-365',
'Sensor-370',
'Sensor-371',
'Sensor-372',
```

```
'Sensor-373',
'Sensor-374',
'Sensor-375',
'Sensor-376',
'Sensor-379',
'Sensor-380',
'Sensor-381',
'Sensor-382',
'Sensor-395',
'Sensor-396',
'Sensor-397',
'Sensor-398',
'Sensor-399',
'Sensor-400',
'Sensor-401',
'Sensor-402',
'Sensor-403',
'Sensor-404',
'Sensor-405',
'Sensor-415',
'Sensor-423',
'Sensor-450',
'Sensor-451',
'Sensor-452',
'Sensor-459',
'Sensor-462',
'Sensor-463',
'Sensor-464',
'Sensor-465',
'Sensor-466',
'Sensor-467',
'Sensor-479',
'Sensor-482',
'Sensor-499',
'Sensor-502',
'Sensor-503',
'Sensor-504',
'Sensor-505',
'Sensor-506',
'Sensor-507',
'Sensor-508',
'Sensor-509',
'Sensor-510',
'Sensor-513',
'Sensor-514',
'Sensor-515',
'Sensor-516',
```

```
 'Sensor-529',
 'Sensor-530',
 'Sensor-531',
 'Sensor-532',
 'Sensor-533',
 'Sensor-534',
 'Sensor-535',
 'Sensor-536',
 'Sensor-537',
 'Sensor-538',
 'Sensor-539',
 'Wafer']
```

[ ]:
```
def get_redundant_cols(df: pd.DataFrame, missing_thresh=.7):
    """
    Returns a list of columns having missing values more than certain thresh.
    """
    cols_missing_ratios = df.isna().sum().div(df.shape[0])
    cols_to_drop = list(cols_missing_ratios[cols_missing_ratios >␣
 ↪missing_thresh].index)
    return cols_to_drop
```

[ ]:
```
## Columns w missing vals more than 70%

cols_to_drop_1 = get_redundant_cols(wafers, missing_thresh=.7)
cols_to_drop_1
```

[ ]:
```
['Sensor-158', 'Sensor-159', 'Sensor-293', 'Sensor-294']
```

[ ]:
```
## Cols to drop

cols_to_drop = cols_to_drop_1 + cols_to_drop_2
```

# 7 4. Feature Selection

[ ]:
```
## Separate features and Labels out

X, y = wafers.drop(cols_to_drop, axis=1), wafers[["Good/Bad"]]
## Dependent feature variables

print("Shape of the features now: ", X.shape)
X.head()
```

```
Shape of the features now:  (100, 465)
```

[ ]:
```
   Sensor-1  Sensor-2   Sensor-3   Sensor-4  Sensor-5  Sensor-7  Sensor-8
0   2968.33   2476.58  2216.7333  1748.0885    1.1127   97.5822    0.1242  \
```

```
1   2961.04   2506.43  2170.0666  1364.5157    1.5447   96.7700    0.1230
2   3072.03   2500.68  2205.7445  1363.1048    1.0518  101.8644    0.1220
3   3021.83   2419.83  2205.7445  1363.1048    1.0518  101.8644    0.1220
4   3006.95   2435.34  2189.8111  1084.6502    1.1993  104.8856    0.1234

   Sensor-9  Sensor-10  Sensor-11  …  Sensor-582  Sensor-583  Sensor-584  \
0    1.5300    -0.0279    -0.0040  …         NaN      0.5004      0.0120
1    1.3953     0.0084     0.0062  …         NaN      0.4994      0.0115
2    1.3896     0.0138     0.0000  …         NaN      0.4987      0.0118
3    1.4108    -0.0046    -0.0024  …         NaN      0.4934      0.0123
4    1.5094    -0.0046     0.0121  …         NaN      0.4987      0.0145

   Sensor-585  Sensor-586  Sensor-587  Sensor-588  Sensor-589  Sensor-590  \
0      0.0033      2.4069      0.0545      0.0184      0.0055     33.7876
1      0.0031      2.3020      0.0545      0.0184      0.0055     33.7876
2      0.0036      2.3719      0.0545      0.0184      0.0055     33.7876
3      0.0040      2.4923      0.0545      0.0184      0.0055     33.7876
4      0.0041      2.8991      0.0545      0.0184      0.0055     33.7876

   Good/Bad
0        -1
1         1
2        -1
3        -1
4        -1

[5 rows x 465 columns]
```

[ ]:
```python
# Independent/Target Variables

print("Shape of the labels: ", y.shape)
y.head()
```

```
Shape of the labels:  (100, 1)
```

[ ]:
```
   Good/Bad
0        -1
1         1
2        -1
3        -1
4        -1
```

# 8 5. Data Transformation

[ ]:
```python
imputer = KNNImputer(n_neighbors=3)
preprocessing_pipeline = Pipeline(
    steps=[('Imputer', imputer), ('Scaler', RobustScaler())])
preprocessing_pipeline
```

[ ]:
```
Pipeline(steps=[('Imputer', KNNImputer(n_neighbors=3)),
                ('Scaler', RobustScaler())])
```

[ ]:
```python
## Transform "Wafers" features

X_trans = preprocessing_pipeline.fit_transform(X)
print("Shape of transformed features set: ", X_trans.shape)
X_trans
```

```
Shape of transformed features set:  (100, 465)
```

[ ]:
```
array([[-0.37110152, -0.21388855,  0.67805794, …,  0.515625  ,
        -0.40093   ,  0.        ],
       [-0.44644841,  0.15494872, -1.32959552, …,  0.515625  ,
        -0.40093   ,  2.        ],
       [ 0.70070541,  0.08389967,  0.20530751, …,  0.515625  ,
        -0.40093   ,  0.        ],
       …,
       [ 0.83289837, -1.31558137, -1.26792905, …, -0.671875  ,
        -0.44021198,  0.        ],
       [-0.49988372,  0.59310515, -0.16308229, …, -0.671875  ,
        -0.44021198,  0.        ],
       [-0.92374874, -0.35561596,  0.40033513, …, -0.671875  ,
        -0.44021198,  2.        ]])
```

# 9 6. Clsutering

[ ]:
```python
from sklearn.cluster import KMeans
from kneed import KneeLocator
from typing import Tuple
from dataclasses import dataclass

@dataclass
class ClusterDataInstances:
    """Divides the given data instances into different clusters via KMeans␣
 ↪Clustering algorithm.

    Args:
        X (np.array): Takes in an array which gotta be clustered.
        desc (str): Description of the said array.
```

```
    """
    X: np.array
    desc: str

    def _get_ideal_number_of_clusters(self):
        """Returns the ideal number of clusters the given data instances should␣
↪be divided into by
        locating the dispersal point in number of clusters vs WCSS plot.

        Raises:
            e: Raises relevant exception should any kinda error pops up while␣
↪determining the ideal
            number of clusters.

        Returns:
            int: Ideal number of clusters the given data instances should be␣
↪divided into.
        """
        try:
            print(
                f'Getting the ideal number of clusters to cluster "{self.desc}␣
↪set" into..')

            ####################### Compute WCSS for shortlisted number of␣
↪clusters ##########################
            print("computing WCSS for shortlisted number of clusters..")
            wcss = []  # Within Summation of Squares
            for i in range(1, 11):
                kmeans = KMeans(n_clusters=i, init='k-means++',
                                random_state=42)
                kmeans.fit(self.X)
                wcss.append(kmeans.inertia_)
                print(f"WCSS for n_clusters={i}: {kmeans.inertia_}")
            print(
                "WCSS computed successfully for all shortlisted number of␣
↪clusters!")

            ################### Finalize dispersal point as the ideal number of␣
↪clusters #####################
            print(
                "Finding the ideal number of clusters (by locating the␣
↪dispersal point) via Elbow method..")
            knee_finder = KneeLocator(
                range(1, 11), wcss, curve='convex', direction='decreasing')  #␣
↪range(1, 11) vs WCSS
            print(
```

```
                f"Ideal number of clusters to be formed: {knee_finder.knee}")

            return knee_finder.knee
            ...
        except Exception as e:
            print(e)
            raise e

    def create_clusters(self) -> Tuple:
        """Divides the given data instances into the different clusters, they␣
↪first hand shoud've been divided into
        via offcourse Kmeans Clustering algorithm.

        Raises:
            e: Raises relevant exception should any kinda error pops up while␣
↪dividing the given data instances into
            clusters.

        Returns:
            (KMeans, np.array): KMeans Clustering object being used to cluster␣
↪the given data instances and the given dataset
            along with the cluster labels, respectively.
        """
        try:
            ideal_clusters = self._get_ideal_number_of_clusters()
            print(
                f"Dividing the \"{self.desc}\" instances into {ideal_clusters}␣
↪clusters via KMeans Clustering algorithm..")
            kmeans = KMeans(n_clusters=ideal_clusters,
                            init='k-means++', random_state=42)
            y_kmeans = kmeans.fit_predict(self.X)
            print(
                f"..said data instances divided into {ideal_clusters} clusters␣
↪successfully!")

            return kmeans, np.c_[self.X, y_kmeans]
            ...
        except Exception as e:
            print(e)
            raise e
```

[ ]:
```
## Cluster `Wafer` instances

cluster_wafers = ClusterDataInstances(X=X_trans, desc="wafers features")
clusterer, X_clus = cluster_wafers.create_clusters()
X_clus
```

```
Getting the ideal number of clusters to cluster "wafers features set" into..
computing WCSS for shortlisted number of clusters..
WCSS for n_clusters=1: 1503049.6472606934
WCSS for n_clusters=2: 512194.0849012661
WCSS for n_clusters=3: 185195.115933283
WCSS for n_clusters=4: 143033.25783274247
WCSS for n_clusters=5: 108688.31540145789
WCSS for n_clusters=6: 88439.04360341988
WCSS for n_clusters=7: 81079.41259322355
WCSS for n_clusters=8: 68622.79634876264
WCSS for n_clusters=9: 61805.448381217175
WCSS for n_clusters=10: 58870.60322516474
WCSS computed successfully for all shortlisted number of clusters!
Finding the ideal number of clusters (by locating the dispersal point) via Elbow
method..
Ideal number of clusters to be formed: 3
Dividing the "wafers features" instances into 3 clusters via KMeans Clustering
algorithm..
..said data instances divided into 3 clusters successfully!
```

[ ]:
```
array([[-0.37110152, -0.21388855,  0.67805794, …, -0.40093   ,
          0.        ,  0.        ],
       [-0.44644841,  0.15494872, -1.32959552, …, -0.40093   ,
          2.        ,  0.        ],
       [ 0.70070541,  0.08389967,  0.20530751, …, -0.40093   ,
          0.        ,  0.        ],
       …,
       [ 0.83289837, -1.31558137, -1.26792905, …, -0.44021198,
          0.        ,  0.        ],
       [-0.49988372,  0.59310515, -0.16308229, …, -0.44021198,
          0.        ,  0.        ],
       [-0.92374874, -0.35561596,  0.40033513, …, -0.44021198,
          2.        ,  0.        ]])
```

[ ]:
```
## Clusters

np.unique(X_clus[:, -1])
```

[ ]:
```
array([0., 1., 2.])
```

- **The datasets is divided into 3 cluster**

[ ]:
```
## Configure "Clustered" array along with target features
wafers_clus = np.c_[X_clus, y]

## Cluster_1 data
wafers_1 = wafers_clus[wafers_clus[:, -2] == 0]
wafers_1.shape
```

[ ]: (96, 467)

- **Perhaps we were wrong about dividing the `Wafers` dataset into clusters, as we can see pretty much of all datapoints lie in the first cluster itself.**

Let's take look at another clusters anyway..

[ ]:
```
## Cluster_2 data

wafers_clus[wafers_clus[:, -2] == 1].shape
```

[ ]: (3, 467)

[ ]:
```
## Cluster_3 data

wafers_clus[wafers_clus[:, -2] == 2].shape
```

[ ]: (1, 467)

- **Thus we mustn't divide the dataset into clusters. Not a good idea!**

## 10 7. Reasamplig Datasets

[ ]:
```
X, y = X_trans[:, :-1], y
resampler = SMOTETomek(sampling_strategy="auto")
X_res, y_res = resampler.fit_resample(X, y)
```

[ ]:
```
print("Before resampling, Shape of training instances: ", np.c_[X, y].shape)
print("After resampling, Shape of training instances: ", np.c_[X_res, y_res].
 ↪shape)
```

```
Before resampling, Shape of training instances:  (100, 465)
After resampling, Shape of training instances:  (188, 465)
```

[ ]:
```
## Target Cats after Resampling

print(np.unique(y_res))
print(f"Value Counts: \n-1: {len(y_res[y_res == -1])}, 1: {len(y_res[y_res ==␣
 ↪1])}")
```

```
[-1  1]
Value Counts:
-1: 188, 1: 188
```

# 11 8. Model Training

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size=1/
    ↪3, random_state=42)

print(f"train set: {X_train.shape, y_train.shape}")
print(f"test set: {X_test.shape, y_test.shape}")
```

```
train set: ((125, 464), (125, 1))
test set: ((63, 464), (63, 1))
```

[ ]:
```
# Prepared training and test sets

X_prep = X_train
y_prep = y_train
X_test_prep = X_test
y_test_prep = y_test

print(X_prep.shape, y_prep.shape)
print(X_test_prep.shape, y_test_prep.shape)
```

```
(125, 464) (125, 1)
(63, 464) (63, 1)
```

[ ]:
```
 #Shortlisted base Models
svc_clf = SVC(kernel='linear')
svc_rbf_clf = SVC(kernel='rbf')
random_clf = RandomForestClassifier(random_state=42)
xgb_clf = XGBClassifier(objective='binary:logistic')
```

[ ]:
```
## A function to display Scores

def display_scores(scores):
    print("Scores: ", scores)
    print("Mean: ", scores.mean())
    print("Standard Deviation: ", scores.std())
```

## 11.1 8.1 SVC (Kernel='linear')

[ ]:
```
## SVC Scores

svc_scores = cross_val_score(svc_clf, X_prep, y_prep, scoring='roc_auc', cv=10,␣
    ↪verbose=2)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.1s remaining:    0.0s
```

```
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
```

```
[CV] END … total time=   0.2s
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
[CV] END … total time=   0.2s

[Parallel(n_jobs=1)]: Done  10 out of  10 | elapsed:    1.0s finished
```

[ ]:
```
display_scores(svc_scores)
```

```
Scores:  [1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
Mean:  1.0
Standard Deviation:  0.0
```

[ ]:
```
## Performance on test set using cross-validation

# Predictions using cross-validation
svc_preds = cross_val_predict(svc_clf, X_test_prep, y_test_prep, cv=5)

# AUC score
svc_auc = roc_auc_score(y_test_prep, svc_preds)
svc_auc
```

[ ]: 0.9558823529411764

### 11.2 8.2 SVC (kerne='rbf')

[ ]:
```
## SVC rbf Scores

svc_rbf_scores = cross_val_score(svc_rbf_clf, X_prep, y_prep,␣
↪scoring='roc_auc', cv=10, verbose=2)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.1s remaining:    0.0s

[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s
[CV] END … total time=   0.1s

[Parallel(n_jobs=1)]: Done  10 out of  10 | elapsed:    0.9s finished
```

[ ]:
```
display_scores(svc_rbf_scores)
```

```
Scores:  [1.         1.         1.         1.         1.         1.
 1.         1.         0.94444444 0.97222222]
Mean:  0.9916666666666668
Standard Deviation:  0.01778645621509121
```

[ ]:
```
## Performance on test set using cross-validation

# Predictions using cross-validation
svc_rbf_preds = cross_val_predict(svc_rbf_clf, X_test_prep, y_test_prep, cv=5)

# AUC score
svc_rbf_auc = roc_auc_score(y_test_prep, svc_rbf_preds)
svc_rbf_auc
```

[ ]:
```
0.9508113590263692
```

### 11.3 8.3 RandomForestClassifier

[ ]:
```
## Random Forest Scores

random_clf_scores = cross_val_score(random_clf, X_prep, y_prep,␣
 ↪scoring='roc_auc', cv=10, verbose=2)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

[CV] END … total time=   1.6s

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    1.6s remaining:    0.0s

[CV] END … total time=   2.3s
[CV] END … total time=   1.4s
[CV] END … total time=   1.4s
[CV] END … total time=   1.6s
[CV] END … total time=   1.5s
[CV] END … total time=   1.4s
[CV] END … total time=   1.6s
[CV] END … total time=   1.7s
[CV] END … total time=   1.6s

[Parallel(n_jobs=1)]: Done  10 out of  10 | elapsed:   16.3s finished
```

[ ]:
```
display_scores(random_clf_scores)
```

```
Scores:  [1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
Mean:  1.0
Standard Deviation:  0.0
```

[ ]:
```
## Performance on test set using cross-validation
```

```python
# Predictions using cross-validation
random_clf_preds = cross_val_predict(random_clf, X_test_prep, y_test_prep, cv=5)

# AUC score
random_clf_auc = roc_auc_score(y_test_prep, random_clf_preds)
random_clf_auc
```

[ ]: 1.0