

# Notebook

November 9, 2025

```
[1]: import pandas as pd
import scipy.stats as stats
```

```
[2]: df = pd.read_csv("data/original-data.csv")
df.rename(columns={'V1': 'X_Minimum'}, inplace=True)
df.rename(columns={'V2': 'X_Maximum'}, inplace=True)
df.rename(columns={'V3': 'Y_Minimum'}, inplace=True)
df.rename(columns={'V4': 'Y_Maximum'}, inplace=True)
df.rename(columns={'V5': 'Pixels_Areas'}, inplace=True)
df.rename(columns={'V6': 'X_Perimeter'}, inplace=True)
df.rename(columns={'V7': 'Y_Perimeter'}, inplace=True)
df.rename(columns={'V8': 'Sum_of_Luminosity'}, inplace=True)
df.rename(columns={'V9': 'Minimum_of_Luminosity'}, inplace=True)
df.rename(columns={'V10': 'Maximum_of_Luminosity'}, inplace=True)
df.rename(columns={'V11': 'Length_of_Conveyer'}, inplace=True)
df.rename(columns={'V12': 'TypesOfSteel_A300'}, inplace=True)
df.rename(columns={'V13': 'TypesOfSteel_A400'}, inplace=True)
df.rename(columns={'V14': 'Steel_Plate_Thickness'}, inplace=True)
df.rename(columns={'V15': 'Edges_Index'}, inplace=True)
df.rename(columns={'V16': 'Empty_Index'}, inplace=True)
df.rename(columns={'V17': 'Square_Index'}, inplace=True)
df.rename(columns={'V18': 'Outside_X_Index'}, inplace=True)
df.rename(columns={'V19': 'Edges_X_Index'}, inplace=True)
df.rename(columns={'V20': 'Edges_Y_Index'}, inplace=True)
df.rename(columns={'V21': 'Outside_Global_Index'}, inplace=True)
df.rename(columns={'V22': 'LogOfAreas'}, inplace=True)
df.rename(columns={'V23': 'Log_X_Index'}, inplace=True)
df.rename(columns={'V24': 'Log_Y_Index'}, inplace=True)
df.rename(columns={'V25': 'Orientation_Index'}, inplace=True)
df.rename(columns={'V26': 'Luminosity_Index'}, inplace=True)
df.rename(columns={'V27': 'SigmoidOfAreas'}, inplace=True)
df.rename(columns={'V28': 'Pastry'}, inplace=True)
df.rename(columns={'V29': 'Z_Scratch'}, inplace=True)
df.rename(columns={'V30': 'K_Scratch'}, inplace=True)
df.rename(columns={'V31': 'Stains'}, inplace=True)
df.rename(columns={'V32': 'Dirtiness'}, inplace=True)
df.rename(columns={'V33': 'Bumps'}, inplace=True)
df.rename(columns={'Class': 'Class'}, inplace=True) # Other_Faults
```

df

```
[2]:
```

	X_Minimum	X_Maximum	Y_Minimum	Y_Maximum	Pixels_Areas	X_Perimeter	\
0	42	50	270900	270944	267	17	
1	645	651	2538079	2538108	108	10	
2	829	835	1553913	1553931	71	8	
3	853	860	369370	369415	176	13	
4	1289	1306	498078	498335	2409	60	
...	...	...	...	...	...	...	
1936	249	277	325780	325796	273	54	
1937	144	175	340581	340598	287	44	
1938	145	174	386779	386794	292	40	
1939	137	170	422497	422528	419	97	
1940	1261	1281	87951	87967	103	26	

	Y_Perimeter	Sum_of_Luminosity	Minimum_of_Luminosity	\
0	44	24220	76	
1	30	11397	84	
2	19	7972	99	
3	45	18996	99	
4	260	246930	37	
...	...	...	...	
1936	22	35033	119	
1937	24	34599	112	
1938	22	37572	120	
1939	47	52715	117	
1940	22	11682	101	

	Maximum_of_Luminosity	...	Orientation_Index	Luminosity_Index	\
0	108	...	0.8182	-0.2913	
1	123	...	0.7931	-0.1756	
2	125	...	0.6667	-0.1228	
3	126	...	0.8444	-0.1568	
4	126	...	0.9338	-0.1992	
...	...	...	...	...	
1936	141	...	-0.4286	0.0026	
1937	133	...	-0.4516	-0.0582	
1938	140	...	-0.4828	0.0052	
1939	140	...	-0.0606	-0.0171	
1940	133	...	-0.2000	-0.1139	

	SigmoidOfAreas	Pastry	Z_Scratch	K_Scratch	Stains	Dirtiness	Bumps	\
0	0.5822	1	0	0	0	0	0	
1	0.2984	1	0	0	0	0	0	
2	0.2150	1	0	0	0	0	0	
3	0.5212	1	0	0	0	0	0	
4	1.0000	1	0	0	0	0	0	

...	...	...	...	...	...	...	...	...
1936	0.7254	0	0	0	0	0	0	0
1937	0.8173	0	0	0	0	0	0	0
1938	0.7079	0	0	0	0	0	0	0
1939	0.9919	0	0	0	0	0	0	0
1940	0.5296	0	0	0	0	0	0	0

	Class
0	1
1	1
2	1
3	1
4	1

...	...
1936	2
1937	2
1938	2
1939	2
1940	2

[1941 rows x 34 columns]

```
[3]: df.duplicated().any()
```

```
[3]: np.False_
```

No duplicates

## 1 Z-Score outlier detection

```
[4]: # All Columns except the ones we're predicting ('Pastry', 'Z_Scratch',
      ↪ 'K_Scratch', 'Stains', 'Dirtiness', 'Bumps', 'Other_Faults_(Class)')
columns_to_check_outliers = [
    'X_Minimum', 'X_Maximum', 'Y_Minimum', 'Y_Maximum', 'Pixels_Areas',
    ↪ 'X_Perimeter',
    'Y_Perimeter', 'Sum_of_Luminosity', 'Minimum_of_Luminosity',
    ↪ 'Maximum_of_Luminosity',
    'Length_of_Conveyer', 'TypesOfSteel_A300', 'TypesOfSteel_A400',
    ↪ 'Steel_Plate_Thickness',
    'Edges_Index', 'Empty_Index', 'Square_Index', 'Outside_X_Index',
    ↪ 'Edges_X_Index',
    'Edges_Y_Index', 'Outside_Global_Index', 'LogOfAreas', 'Log_X_Index',
    ↪ 'Log_Y_Index',
    'Orientation_Index', 'Luminosity_Index', 'SigmoidOfAreas'
]
# Ignoring certain columns without outliers - to use a more aggressive outlier
↪ detection on the others
```

```

columns_to_ignore = [
    'X_Minimum', 'X_Maximum', 'Length_of_Conveyer', 'TypesOfSteel_A300',
    ↪ 'TypesOfSteel_A400',
    'Edges_Index', 'Square_Index', 'Edges_X_Index', 'Edges_Y_Index',
    ↪ 'Outside_Global_Index',
    'Orientation_Index', 'SigmoidOfAreas'
]
columns_to_check_outliers = [col for col in columns_to_check_outliers if col
    ↪ not in columns_to_ignore]
print(columns_to_check_outliers)
z_score = stats.zscore(df[columns_to_check_outliers])
df_clean = df.copy()
df_clean = df_clean[(abs(z_score) < 4).all(axis=1)]

```

```

['Y_Minimum', 'Y_Maximum', 'Pixels_Areas', 'X_Perimeter', 'Y_Perimeter',
'Sum_of_Luminosity', 'Minimum_of_Luminosity', 'Maximum_of_Luminosity',
'Steel_Plate_Thickness', 'Empty_Index', 'Outside_X_Index', 'LogOfAreas',
'Log_X_Index', 'Log_Y_Index', 'Luminosity_Index']

```

## 2 Modifikovaná 5% 95% Metóda

```

[5]: # All Columns except the ones we're predicting ('Pastry', 'Z_Scratch',
    ↪ 'K_Scratch', 'Stains', 'Dirtiness', 'Bumps', 'Other_Faults_(Class)')
columns_to_check_outliers = [
    'X_Minimum', 'X_Maximum', 'Y_Minimum', 'Y_Maximum', 'Pixels_Areas',
    ↪ 'X_Perimeter',
    'Y_Perimeter', 'Sum_of_Luminosity', 'Minimum_of_Luminosity',
    ↪ 'Maximum_of_Luminosity',
    'TypesOfSteel_A300', 'TypesOfSteel_A400', 'Steel_Plate_Thickness',
    ↪ 'Edges_Index',
    'Empty_Index', 'Square_Index', 'Outside_X_Index', 'Edges_X_Index',
    ↪ 'Edges_Y_Index',
    'Outside_Global_Index', 'LogOfAreas', 'Log_X_Index', 'Log_Y_Index',
    ↪ 'Orientation_Index',
    'Luminosity_Index', 'SigmoidOfAreas'
]
# Ignoring certain columns without outliers - to use a more aggressive outlier
    ↪ detection on the others
columns_to_ignore = [
    'X_Minimum', 'X_Maximum', 'Length_of_Conveyer', 'TypesOfSteel_A300',
    ↪ 'TypesOfSteel_A400',
    'Edges_Index', 'Square_Index', 'Edges_X_Index', 'Edges_Y_Index',
    ↪ 'Outside_Global_Index',
    'Orientation_Index', 'SigmoidOfAreas',
    # Ignoring columns that were well handled by Z-Score already or don't
    ↪ require more cleaning

```

```

        'Y_Minimum', 'Y_Maximum', 'Minimum_of_Luminosity', 'Maximum_of_Luminosity',
        'Steel_Plate_Thickness', 'Empty_Index',
        'Log_X_Index', 'Log_Y_Index', 'Luminosity_Index'
    ]
    columns_to_check_outliers = [col for col in columns_to_check_outliers if col
        not in columns_to_ignore]
    print(columns_to_check_outliers)

    shaving_ranges = [
        (0.0, 0.98), (0.0, 0.98), (0.0, 0.98), (0.0, 0.98), (0.0, 0.98), (0.0, 0.98)
    ]

    for idx, col in enumerate(columns_to_check_outliers):
        lower = 0
        higher = 1
        df_CO_lower = df_clean[col].quantile(shaving_ranges[idx][lower])
        df_CO_upper = df_clean[col].quantile(shaving_ranges[idx][higher])

        df_clean[col] = df[col].where(
            (df_clean[col] >= df_CO_lower) & (df_clean[col] <= df_CO_upper)
        )
        df_clean.dropna(inplace = True)

```

```

['Pixels_Areas', 'X_Perimeter', 'Y_Perimeter', 'Sum_of_Luminosity',
'Outside_X_Index', 'LogOfAreas']

```

```

[6]: df_clean = df_clean.drop(columns=["Y_Minimum", "Y_Maximum", "Edges_Index",
        "Empty_Index"], errors="ignore")
df_clean.describe()

```

```

[6]:
      X_Minimum  X_Maximum  Pixels_Areas  X_Perimeter  Y_Perimeter  \
count  1613.000000  1613.000000  1613.000000  1613.000000  1613.000000
mean    629.401116   655.522009   632.513329    48.324241   39.787353
std     517.427471   507.119546  1334.099392    64.058738   47.378852
min       0.000000     4.000000     2.000000     2.000000     1.000000
25%     114.000000    181.000000     77.000000    14.000000    12.000000
50%     563.000000    583.000000    141.000000    22.000000    21.000000
75%    1090.000000   1106.000000    349.000000    47.000000    42.000000
max    1705.000000   1713.000000   6277.000000   405.000000   330.000000

      Sum_of_Luminosity  Minimum_of_Luminosity  Maximum_of_Luminosity  \
count      1613.000000      1613.000000      1613.000000
mean      66874.983881         90.650961      129.055797
std     139509.821414         27.155015       16.596791
min         250.000000          0.000000       70.000000
25%         8602.000000         77.000000      124.000000
50%        16182.000000         95.000000      127.000000

```

75%	37460.000000	109.000000	135.000000
max	652005.000000	179.000000	199.000000

	Length_of_Conveyer	TypesOfSteel_A300	...	Orientation_Index	\
count	1613.000000	1613.000000	...	1613.000000	
mean	1468.679479	0.456293	...	0.121622	
std	150.098130	0.498240	...	0.495092	
min	1227.000000	0.000000	...	-0.970600	
25%	1358.000000	0.000000	...	-0.250000	
50%	1364.000000	0.000000	...	0.153900	
75%	1656.000000	1.000000	...	0.545400	
max	1794.000000	1.000000	...	0.946700	

	Luminosity_Index	SigmoidOfAreas	Pastry	Z_Scratch	\
count	1613.000000	1613.000000	1613.000000	1613.000000	
mean	-0.131680	0.524665	0.091754	0.115313	
std	0.140006	0.321606	0.288769	0.319498	
min	-0.609600	0.119000	0.000000	0.000000	
25%	-0.199500	0.230000	0.000000	0.000000	
50%	-0.132600	0.402500	0.000000	0.000000	
75%	-0.057500	0.897100	0.000000	0.000000	
max	0.457300	1.000000	1.000000	1.000000	

	K_Scratch	Stains	Dirtiness	Bumps	Class
count	1613.000000	1613.000000	1613.000000	1613.000000	1613.000000
mean	0.106634	0.044637	0.034098	0.243025	1.364538
std	0.308743	0.206570	0.181537	0.429043	0.481450
min	0.000000	0.000000	0.000000	0.000000	1.000000
25%	0.000000	0.000000	0.000000	0.000000	1.000000
50%	0.000000	0.000000	0.000000	0.000000	1.000000
75%	0.000000	0.000000	0.000000	0.000000	2.000000
max	1.000000	1.000000	1.000000	1.000000	2.000000

[8 rows x 30 columns]

```
[7]: feature_cols = [*df_clean.columns[:len(df_clean.columns)-7]]
      feature_cols
```

```
[7]: ['X_Minimum',
      'X_Maximum',
      'Pixels_Areas',
      'X_Perimeter',
      'Y_Perimeter',
      'Sum_of_Luminosity',
      'Minimum_of_Luminosity',
      'Maximum_of_Luminosity',
      'Length_of_Conveyer',
```

```

'TypesOfSteel_A300',
'TypesOfSteel_A400',
'Steel_Plate_Thickness',
'Square_Index',
'Outside_X_Index',
'Edges_X_Index',
'Edges_Y_Index',
'Outside_Global_Index',
'LogOfAreas',
'Log_X_Index',
'Log_Y_Index',
'Orientation_Index',
'Luminosity_Index',
'SigmoidOfAreas']

```

```

[8]: predict_cols = ["Pastry", "Z_Scratch", "K_Scratch", "K_Scratch", "Stains",
↪ "Dirtiness", "Bumps", "Class"]

```

```

[9]: df_clean["Class"].nunique()

```

```

[9]: 2

```

```

[10]: df_clean

```

```

[10]:
      X_Minimum  X_Maximum  Pixels_Areas  X_Perimeter  Y_Perimeter  \
0             42         50         267.0          17.0          44.0
1          645         651         108.0          10.0          30.0
2          829         835          71.0           8.0          19.0
3          853         860         176.0          13.0          45.0
4         1289        1306        2409.0          60.0         260.0
...         ...         ...         ...         ...         ...
1936         249         277         273.0          54.0          22.0
1937         144         175         287.0          44.0          24.0
1938         145         174         292.0          40.0          22.0
1939         137         170         419.0          97.0          47.0
1940        1261        1281         103.0          26.0          22.0

      Sum_of_Luminosity  Minimum_of_Luminosity  Maximum_of_Luminosity  \
0             24220.0              76              108
1             11397.0              84              123
2              7972.0              99              125
3             18996.0              99              126
4            246930.0              37              126
...         ...         ...         ...
1936            35033.0             119              141
1937            34599.0             112              133
1938            37572.0             120              140

```

1939	52715.0	117	140
1940	11682.0	101	133

	Length_of_Conveyer	TypesOfSteel_A300	...	Orientation_Index	\
0	1687	1	...	0.8182	
1	1687	1	...	0.7931	
2	1623	1	...	0.6667	
3	1353	0	...	0.8444	
4	1353	0	...	0.9338	
...	...	...	...	...	
1936	1360	0	...	-0.4286	
1937	1360	0	...	-0.4516	
1938	1360	0	...	-0.4828	
1939	1360	0	...	-0.0606	
1940	1360	1	...	-0.2000	

  

	Luminosity_Index	SigmoidOfAreas	Pastry	Z_Scratch	K_Scratch	Stains	\
0	-0.2913	0.5822	1	0	0	0	
1	-0.1756	0.2984	1	0	0	0	
2	-0.1228	0.2150	1	0	0	0	
3	-0.1568	0.5212	1	0	0	0	
4	-0.1992	1.0000	1	0	0	0	
...	...	...	...	...	...		
1936	0.0026	0.7254	0	0	0	0	
1937	-0.0582	0.8173	0	0	0	0	
1938	0.0052	0.7079	0	0	0	0	
1939	-0.0171	0.9919	0	0	0	0	
1940	-0.1139	0.5296	0	0	0	0	

	Dirtiness	Bumps	Class
0	0	0	1
1	0	0	1
2	0	0	1
3	0	0	1
4	0	0	1
...	...	...	
1936	0	0	2
1937	0	0	2
1938	0	0	2
1939	0	0	2
1940	0	0	2

[1613 rows x 30 columns]

```
[11]: normalized_df = (df_clean[feature_cols] - df_clean[feature_cols].mean())/
      ↪ df_clean[feature_cols].std()
```



```
[12]: normalized_df
```

```
[12]:
```

	X_Minimum	X_Maximum	Pixels_Areas	X_Perimeter	Y_Perimeter	\
0	-1.135234	-1.194042	-0.273978	-0.488992	0.088914	
1	0.030147	-0.008917	-0.393159	-0.598267	-0.206576	
2	0.385752	0.353917	-0.420893	-0.629489	-0.438747	
3	0.432136	0.403215	-0.342188	-0.551435	0.110021	
4	1.274766	1.282692	1.331600	0.182266	4.647910	
...	...	...	...	...	...	
1936	-0.735178	-0.746416	-0.269480	0.088602	-0.375428	
1937	-0.938105	-0.947552	-0.258986	-0.067504	-0.333215	
1938	-0.936172	-0.949524	-0.255238	-0.129947	-0.375428	
1939	-0.951633	-0.957411	-0.160043	0.759861	0.152233	
1940	1.220652	1.233394	-0.396907	-0.348496	-0.375428	

  

	Sum_of_Luminosity	Minimum_of_Luminosity	Maximum_of_Luminosity	\
0	-0.305749	-0.539531	-1.268667	
1	-0.397664	-0.244926	-0.364878	
2	-0.422214	0.307458	-0.244372	
3	-0.343194	0.307458	-0.184120	
4	1.290626	-1.975729	-0.184120	
...	...	...	...	
1936	-0.228242	1.043971	0.719669	
1937	-0.231353	0.786191	0.237649	
1938	-0.210042	1.080796	0.659417	
1939	-0.101498	0.970319	0.659417	
1940	-0.395621	0.381110	0.237649	

  

	Length_of_Conveyer	TypesOfSteel_A300	...	Outside_X_Index	\
0	1.454519	1.091255	...	-0.514948	
1	1.454519	1.091255	...	-0.556364	
2	1.028131	1.091255	...	-0.552599	
3	-0.770692	-0.915808	...	-0.496123	
4	-0.770692	-0.915808	...	-0.217504	
...	...	...	...	...	
1936	-0.724056	-0.915808	...	0.083706	
1937	-0.724056	-0.915808	...	0.166538	
1938	-0.724056	-0.915808	...	0.110061	
1939	-0.724056	-0.915808	...	0.223015	
1940	-0.724056	1.091255	...	-0.138436	

  

	Edges_X_Index	Edges_Y_Index	Outside_Global_Index	LogOfAreas	\
0	-0.718842	0.695123	0.836722	0.237173	
1	-0.159904	0.526690	0.836722	-0.417695	
2	0.488015	0.429070	0.836722	-0.721056	
3	-0.425551	0.695123	0.836722	-0.064356	
4	-1.527877	0.636955	0.836722	1.828612	

...	...	...	...	...
1936	-0.511940	-0.684202	-1.263874	0.253332
1937	0.291911	-0.780305	-1.263874	0.289482
1938	0.380028	-0.914342	-1.263874	0.301977
1939	-1.282100	-1.026631	-1.263874	0.563191
1940	0.570948	-0.684202	-1.263874	-0.452012

	Log_X_Index	Log_Y_Index	Orientation_Index	Luminosity_Index	\
0	-0.846876	0.865673	1.406965	-1.140097	
1	-1.190733	0.399819	1.356268	-0.313702	
2	-1.190733	-0.132917	1.100962	0.063426	
3	-1.006553	0.890625	1.459885	-0.179421	
4	0.054474	2.837130	1.640457	-0.482266	
...	...	...	...	...	
1936	0.651061	-0.264622	-1.111353	0.959104	
1937	0.772746	-0.196712	-1.157808	0.524836	
1938	0.692907	-0.336648	-1.220827	0.977674	
1939	0.847354	0.474417	-0.368057	0.818395	
1940	0.248564	-0.264622	-0.649621	0.126995	

	SigmoidOfAreas
0	0.178899
1	-0.703548
2	-0.962871
3	-0.010774
4	1.478005
...	...
1936	0.624165
1937	0.909918
1938	0.569750
1939	1.452819
1940	0.015345

[1613 rows x 23 columns]

```
[13]: df2 = normalized_df.join(df[predict_cols], how='inner', lsuffix='_caller',
    ↪rsuffix='_other')
```

```
[14]: df2
```

	X_Minimum	X_Maximum	Pixels_Areas	X_Perimeter	Y_Perimeter	\
0	-1.135234	-1.194042	-0.273978	-0.488992	0.088914	
1	0.030147	-0.008917	-0.393159	-0.598267	-0.206576	
2	0.385752	0.353917	-0.420893	-0.629489	-0.438747	
3	0.432136	0.403215	-0.342188	-0.551435	0.110021	
4	1.274766	1.282692	1.331600	0.182266	4.647910	
...	...	...	...	...	...	

1936	-0.735178	-0.746416	-0.269480	0.088602	-0.375428
1937	-0.938105	-0.947552	-0.258986	-0.067504	-0.333215
1938	-0.936172	-0.949524	-0.255238	-0.129947	-0.375428
1939	-0.951633	-0.957411	-0.160043	0.759861	0.152233
1940	1.220652	1.233394	-0.396907	-0.348496	-0.375428

	Sum_of_Luminosity	Minimum_of_Luminosity	Maximum_of_Luminosity	\
0	-0.305749	-0.539531	-1.268667	
1	-0.397664	-0.244926	-0.364878	
2	-0.422214	0.307458	-0.244372	
3	-0.343194	0.307458	-0.184120	
4	1.290626	-1.975729	-0.184120	
...	...	...	...	
1936	-0.228242	1.043971	0.719669	
1937	-0.231353	0.786191	0.237649	
1938	-0.210042	1.080796	0.659417	
1939	-0.101498	0.970319	0.659417	
1940	-0.395621	0.381110	0.237649	

	Length_of_Conveyer	TypesOfSteel_A300	...	Luminosity_Index	\
0	1.454519	1.091255	...	-1.140097	
1	1.454519	1.091255	...	-0.313702	
2	1.028131	1.091255	...	0.063426	
3	-0.770692	-0.915808	...	-0.179421	
4	-0.770692	-0.915808	...	-0.482266	
...	...	...	...	...	
1936	-0.724056	-0.915808	...	0.959104	
1937	-0.724056	-0.915808	...	0.524836	
1938	-0.724056	-0.915808	...	0.977674	
1939	-0.724056	-0.915808	...	0.818395	
1940	-0.724056	1.091255	...	0.126995	

	SigmoidOfAreas	Pastry	Z_Scratch	K_Scratch	K_Scratch	Stains	\
0	0.178899	1	0	0	0	0	
1	-0.703548	1	0	0	0	0	
2	-0.962871	1	0	0	0	0	
3	-0.010774	1	0	0	0	0	
4	1.478005	1	0	0	0	0	
...	...	...	...	...	...	...	
1936	0.624165	0	0	0	0	0	
1937	0.909918	0	0	0	0	0	
1938	0.569750	0	0	0	0	0	
1939	1.452819	0	0	0	0	0	
1940	0.015345	0	0	0	0	0	

	Dirtiness	Bumps	Class
0	0	0	1

1	0	0	1
2	0	0	1
3	0	0	1
4	0	0	1
...	...	...	...
1936	0	0	2
1937	0	0	2
1938	0	0	2
1939	0	0	2
1940	0	0	2

[1613 rows x 31 columns]

```
[15]: df2["Class"]-=1
df2_multiclass = df2.copy()
```

## 2.1 Feature Selection

### 2.1.1 Random Forest

```
[16]: from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectFromModel

columns_to_ignore = ["Pastry", "Z_Scratch", "K_Scratch", "Stains", "Dirtiness",
                    ↪ "Bumps", "Class"]
df_feature_sel = df2.drop(columns=columns_to_ignore)

# Selecting the target column
target = df2["Class"]

clf = RandomForestClassifier()
clf = clf.fit(df_feature_sel, target)
print(clf.feature_importances_)

model = SelectFromModel(clf, prefit=True)

mask = model.get_support()
selected_columns = df_feature_sel.columns[mask]

df_ranFor = df_feature_sel.loc[:, selected_columns]
```

```
[0.05692419 0.0593691 0.04443948 0.03865951 0.03056805 0.05036666
0.05493708 0.04782427 0.06463809 0.01595412 0.01356195 0.06854246
0.04278322 0.04671546 0.04287257 0.0451143 0.00442681 0.04734333
0.03699062 0.03392335 0.05956042 0.05541509 0.03906988]
```

```
[17]: df_feature_sel
```

```

[17]:      X_Minimum  X_Maximum  Pixels_Areas  X_Perimeter  Y_Perimeter  \
0      -1.135234 -1.194042    -0.273978    -0.488992    0.088914
1       0.030147 -0.008917    -0.393159    -0.598267   -0.206576
2       0.385752  0.353917    -0.420893    -0.629489   -0.438747
3       0.432136  0.403215    -0.342188    -0.551435    0.110021
4       1.274766  1.282692     1.331600     0.182266    4.647910
...      ...      ...      ...      ...      ...
1936   -0.735178 -0.746416    -0.269480     0.088602   -0.375428
1937   -0.938105 -0.947552    -0.258986    -0.067504   -0.333215
1938   -0.936172 -0.949524    -0.255238    -0.129947   -0.375428
1939   -0.951633 -0.957411    -0.160043     0.759861    0.152233
1940    1.220652  1.233394    -0.396907    -0.348496   -0.375428

      Sum_of_Luminosity  Minimum_of_Luminosity  Maximum_of_Luminosity  \
0          -0.305749          -0.539531          -1.268667
1          -0.397664          -0.244926          -0.364878
2          -0.422214           0.307458          -0.244372
3          -0.343194           0.307458          -0.184120
4           1.290626          -1.975729          -0.184120
...      ...      ...      ...
1936         -0.228242           1.043971           0.719669
1937         -0.231353           0.786191           0.237649
1938         -0.210042           1.080796           0.659417
1939         -0.101498           0.970319           0.659417
1940         -0.395621           0.381110           0.237649

      Length_of_Conveyer  TypesOfSteel_A300  ...  Outside_X_Index  \
0           1.454519           1.091255  ...      -0.514948
1           1.454519           1.091255  ...      -0.556364
2           1.028131           1.091255  ...      -0.552599
3          -0.770692          -0.915808  ...      -0.496123
4          -0.770692          -0.915808  ...      -0.217504
...      ...      ...      ...
1936         -0.724056          -0.915808  ...           0.083706
1937         -0.724056          -0.915808  ...           0.166538
1938         -0.724056          -0.915808  ...           0.110061
1939         -0.724056          -0.915808  ...           0.223015
1940         -0.724056           1.091255  ...      -0.138436

      Edges_X_Index  Edges_Y_Index  Outside_Global_Index  LogOfAreas  \
0      -0.718842      0.695123           0.836722      0.237173
1      -0.159904      0.526690           0.836722     -0.417695
2       0.488015      0.429070           0.836722     -0.721056
3      -0.425551      0.695123           0.836722     -0.064356
4      -1.527877      0.636955           0.836722      1.828612
...      ...      ...      ...
1936     -0.511940     -0.684202          -1.263874      0.253332

```

1937	0.291911	-0.780305	-1.263874	0.289482
1938	0.380028	-0.914342	-1.263874	0.301977
1939	-1.282100	-1.026631	-1.263874	0.563191
1940	0.570948	-0.684202	-1.263874	-0.452012

	Log_X_Index	Log_Y_Index	Orientation_Index	Luminosity_Index \
0	-0.846876	0.865673	1.406965	-1.140097
1	-1.190733	0.399819	1.356268	-0.313702
2	-1.190733	-0.132917	1.100962	0.063426
3	-1.006553	0.890625	1.459885	-0.179421
4	0.054474	2.837130	1.640457	-0.482266
...	...	...	...	...
1936	0.651061	-0.264622	-1.111353	0.959104
1937	0.772746	-0.196712	-1.157808	0.524836
1938	0.692907	-0.336648	-1.220827	0.977674
1939	0.847354	0.474417	-0.368057	0.818395
1940	0.248564	-0.264622	-0.649621	0.126995

	SigmoidOfAreas
0	0.178899
1	-0.703548
2	-0.962871
3	-0.010774
4	1.478005
...	...
1936	0.624165
1937	0.909918
1938	0.569750
1939	1.452819
1940	0.015345

[1613 rows x 23 columns]

```
[18]: df_ranFor["Class"] = df2["Class"]
df_ranFor
```

[18]:	X_Minimum	X_Maximum	Pixels_Areas	Sum_of_Luminosity \
0	-1.135234	-1.194042	-0.273978	-0.305749
1	0.030147	-0.008917	-0.393159	-0.397664
2	0.385752	0.353917	-0.420893	-0.422214
3	0.432136	0.403215	-0.342188	-0.343194
4	1.274766	1.282692	1.331600	1.290626
...	...	...	...	...
1936	-0.735178	-0.746416	-0.269480	-0.228242
1937	-0.938105	-0.947552	-0.258986	-0.231353
1938	-0.936172	-0.949524	-0.255238	-0.210042
1939	-0.951633	-0.957411	-0.160043	-0.101498

1940	1.220652	1.233394	-0.396907	-0.395621
------	----------	----------	-----------	-----------

	Minimum_of_Luminosity	Maximum_of_Luminosity	Length_of_Conveyer	\
0	-0.539531	-1.268667	1.454519	
1	-0.244926	-0.364878	1.454519	
2	0.307458	-0.244372	1.028131	
3	0.307458	-0.184120	-0.770692	
4	-1.975729	-0.184120	-0.770692	
...	...	...	...	
1936	1.043971	0.719669	-0.724056	
1937	0.786191	0.237649	-0.724056	
1938	1.080796	0.659417	-0.724056	
1939	0.970319	0.659417	-0.724056	
1940	0.381110	0.237649	-0.724056	

	Steel_Plate_Thickness	Outside_X_Index	Edges_Y_Index	LogOfAreas	\
0	0.035167	-0.514948	0.695123	0.237173	
1	0.035167	-0.556364	0.526690	-0.417695	
2	0.475065	-0.552599	0.429070	-0.721056	
3	4.654098	-0.496123	0.695123	-0.064356	
4	2.344632	-0.217504	0.636955	1.828612	
...	...	...	...	...	
1936	-0.844629	0.083706	-0.684202	0.253332	
1937	-0.844629	0.166538	-0.780305	0.289482	
1938	-0.844629	0.110061	-0.914342	0.301977	
1939	-0.844629	0.223015	-1.026631	0.563191	
1940	0.035167	-0.138436	-0.684202	-0.452012	

	Orientation_Index	Luminosity_Index	Class
0	1.406965	-1.140097	0
1	1.356268	-0.313702	0
2	1.100962	0.063426	0
3	1.459885	-0.179421	0
4	1.640457	-0.482266	0
...	...	...	...
1936	-1.111353	0.959104	1
1937	-1.157808	0.524836	1
1938	-1.220827	0.977674	1
1939	-0.368057	0.818395	1
1940	-0.649621	0.126995	1

[1613 rows x 14 columns]

## 2.2 Saving the Data

```
[19]: df_ranFor
```

```
[19]:
```

	X_Minimum	X_Maximum	Pixels_Areas	Sum_of_Luminosity	\
0	-1.135234	-1.194042	-0.273978	-0.305749	
1	0.030147	-0.008917	-0.393159	-0.397664	
2	0.385752	0.353917	-0.420893	-0.422214	
3	0.432136	0.403215	-0.342188	-0.343194	
4	1.274766	1.282692	1.331600	1.290626	
...	...	...	...	...	
1936	-0.735178	-0.746416	-0.269480	-0.228242	
1937	-0.938105	-0.947552	-0.258986	-0.231353	
1938	-0.936172	-0.949524	-0.255238	-0.210042	
1939	-0.951633	-0.957411	-0.160043	-0.101498	
1940	1.220652	1.233394	-0.396907	-0.395621	

  

	Minimum_of_Luminosity	Maximum_of_Luminosity	Length_of_Conveyer	\
0	-0.539531	-1.268667	1.454519	
1	-0.244926	-0.364878	1.454519	
2	0.307458	-0.244372	1.028131	
3	0.307458	-0.184120	-0.770692	
4	-1.975729	-0.184120	-0.770692	
...	...	...	...	
1936	1.043971	0.719669	-0.724056	
1937	0.786191	0.237649	-0.724056	
1938	1.080796	0.659417	-0.724056	
1939	0.970319	0.659417	-0.724056	
1940	0.381110	0.237649	-0.724056	

  

	Steel_Plate_Thickness	Outside_X_Index	Edges_Y_Index	LogOfAreas	\
0	0.035167	-0.514948	0.695123	0.237173	
1	0.035167	-0.556364	0.526690	-0.417695	
2	0.475065	-0.552599	0.429070	-0.721056	
3	4.654098	-0.496123	0.695123	-0.064356	
4	2.344632	-0.217504	0.636955	1.828612	
...	...	...	...	...	
1936	-0.844629	0.083706	-0.684202	0.253332	
1937	-0.844629	0.166538	-0.780305	0.289482	
1938	-0.844629	0.110061	-0.914342	0.301977	
1939	-0.844629	0.223015	-1.026631	0.563191	
1940	0.035167	-0.138436	-0.684202	-0.452012	

  

	Orientation_Index	Luminosity_Index	Class
0	1.406965	-1.140097	0
1	1.356268	-0.313702	0
2	1.100962	0.063426	0



3	1.459885	-0.179421	0
4	1.640457	-0.482266	0
...	...	...	...
1936	-1.111353	0.959104	1
1937	-1.157808	0.524836	1
1938	-1.220827	0.977674	1
1939	-0.368057	0.818395	1
1940	-0.649621	0.126995	1

[1613 rows x 14 columns]

[20]: df2\_multiclass

[20]:

	X_Minimum	X_Maximum	Pixels_Areas	X_Perimeter	Y_Perimeter	\
0	-1.135234	-1.194042	-0.273978	-0.488992	0.088914	
1	0.030147	-0.008917	-0.393159	-0.598267	-0.206576	
2	0.385752	0.353917	-0.420893	-0.629489	-0.438747	
3	0.432136	0.403215	-0.342188	-0.551435	0.110021	
4	1.274766	1.282692	1.331600	0.182266	4.647910	
...	...	...	...	...	...	
1936	-0.735178	-0.746416	-0.269480	0.088602	-0.375428	
1937	-0.938105	-0.947552	-0.258986	-0.067504	-0.333215	
1938	-0.936172	-0.949524	-0.255238	-0.129947	-0.375428	
1939	-0.951633	-0.957411	-0.160043	0.759861	0.152233	
1940	1.220652	1.233394	-0.396907	-0.348496	-0.375428	

  

	Sum_of_Luminosity	Minimum_of_Luminosity	Maximum_of_Luminosity	\
0	-0.305749	-0.539531	-1.268667	
1	-0.397664	-0.244926	-0.364878	
2	-0.422214	0.307458	-0.244372	
3	-0.343194	0.307458	-0.184120	
4	1.290626	-1.975729	-0.184120	
...	...	...	...	
1936	-0.228242	1.043971	0.719669	
1937	-0.231353	0.786191	0.237649	
1938	-0.210042	1.080796	0.659417	
1939	-0.101498	0.970319	0.659417	
1940	-0.395621	0.381110	0.237649	

  

	Length_of_Conveyer	TypesOfSteel_A300	...	Luminosity_Index	\
0	1.454519	1.091255	...	-1.140097	
1	1.454519	1.091255	...	-0.313702	
2	1.028131	1.091255	...	0.063426	
3	-0.770692	-0.915808	...	-0.179421	
4	-0.770692	-0.915808	...	-0.482266	
...	...	...	...	...	
1936	-0.724056	-0.915808	...	0.959104	

1937	-0.724056	-0.915808	...	0.524836
1938	-0.724056	-0.915808	...	0.977674
1939	-0.724056	-0.915808	...	0.818395
1940	-0.724056	1.091255	...	0.126995

	SigmoidOfAreas	Pastry	Z_Scratch	K_Scratch	K_Scratch	Stains	\
0	0.178899	1	0	0	0	0	
1	-0.703548	1	0	0	0	0	
2	-0.962871	1	0	0	0	0	
3	-0.010774	1	0	0	0	0	
4	1.478005	1	0	0	0	0	
...	...	...	...	...	...	...	
1936	0.624165	0	0	0	0	0	
1937	0.909918	0	0	0	0	0	
1938	0.569750	0	0	0	0	0	
1939	1.452819	0	0	0	0	0	
1940	0.015345	0	0	0	0	0	

	Dirtiness	Bumps	Class
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
1936	0	0	1
1937	0	0	1
1938	0	0	1
1939	0	0	1
1940	0	0	1

[1613 rows x 31 columns]

```
[21]: df_ranFor.to_csv("data/norm_data.csv", index=False)
df2_multiclass.to_csv("data/norm_multiclass_data.csv", index=False)
```