Importing the libraries

In [278]:
```
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
```

In [279]:
```
from sklearn.decomposition import PCA as pca
from sklearn.decomposition import FactorAnalysis as fact
from sklearn import preprocessing
from factor_analyzer import FactorAnalyzer
from varclushi import VarClusHi
```

In [280]:
```
#For the tree
from sklearn.feature_extraction.image import grid_to_graph
from sklearn import tree
from sklearn.externals.six import StringIO
from IPython.display import Image
import pydotplus

from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
from sklearn import metrics

#For displaying the tree
from sklearn.externals.six import StringIO
from IPython.display import Image, display

#Neural Network
from sklearn.neural_network import MLPRegressor
from sklearn.neural_network import MLPClassifier

from sklearn.model_selection import train_test_split
from sklearn import preprocessing

#Multiple Regression
from sklearn.linear_model import LinearRegression
import statsmodels.formula.api as smf

#importing interpretable machine learning
import eli5

from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_curve, roc_auc_score
from matplotlib import pyplot as plt
```

In [281]:
```
#changing jupyter notebook display size
pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)
```

Loading the data file

In [282]:
```
#changing the working directory
os.chdir(r'C:\Users\Anirud Vem\Desktop\Faulty steel plates')
```

In [283]:
```
#loading the data file
df_steel = pd.read_csv('faults.CSV')
```

In [284]:
```
df_steel.head()
```

Out[284]:

	X_Minimum	X_Maximum	Y_Minimum	Y_Maximum	Pixels_Areas	X_Perimeter	Y_Perimeter
0	42	50	270900	270944	267	17	44
1	645	651	2538079	2538108	108	10	30
2	829	835	1553913	1553931	71	8	19
3	853	860	369370	369415	176	13	45
4	1289	1306	498078	498335	2409	60	260

In [285]:
```
df_steel.columns
```

Out[285]:
```
Index(['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', 'TypeOfSteel_A300', 'TypeOfS
teel_A400', 'Steel_Plate_Thickness', 'Edges_Index', 'Empty_Index', 'Square_
Index', 'Outside_X_Index', 'Edges_X_Index', 'Edges_Y_Index', 'Outside_Globa
l_Index', 'LogOfAreas', 'Log_X_Index', 'Log_Y_Index', 'Orientation_Index',
'Luminosity_Index', 'SigmoidOfAreas', 'Pastry', 'Z_Scratch', 'K_Scatch', 'S
tains', 'Dirtiness', 'Bumps', 'Other_Faults'], dtype='object')
```

In [286]:
```
#shape of the data file
df_steel.shape
```

Out[286]:
```
(1941, 34)
```

Describing the data

In [287]:

```
df_steel.describe().T
```

Out[287]:

	count	mean	std	min	25%	
X_Minimum	1941.0	5.711360e+02	5.206907e+02	0.0000	51.0000	4.35
X_Maximum	1941.0	6.179645e+02	4.976274e+02	4.0000	192.0000	4.67
Y_Minimum	1941.0	1.650685e+06	1.774578e+06	6712.0000	471253.0000	1.20
Y_Maximum	1941.0	1.650739e+06	1.774590e+06	6724.0000	471281.0000	1.20
Pixels_Areas	1941.0	1.893878e+03	5.168460e+03	2.0000	84.0000	1.74
X_Perimeter	1941.0	1.118552e+02	3.012092e+02	2.0000	15.0000	2.60
Y_Perimeter	1941.0	8.296600e+01	4.264829e+02	1.0000	13.0000	2.50
Sum_of_Luminosity	1941.0	2.063121e+05	5.122936e+05	250.0000	9522.0000	1.92
Minimum_of_Luminosity	1941.0	8.454869e+01	3.213428e+01	0.0000	63.0000	9.00
Maximum_of_Luminosity	1941.0	1.301937e+02	1.869099e+01	37.0000	124.0000	1.27
Length_of_Conveyer	1941.0	1.459160e+03	1.445778e+02	1227.0000	1358.0000	1.36
TypeOfSteel_A300	1941.0	4.003091e-01	4.900872e-01	0.0000	0.0000	0.00
TypeOfSteel_A400	1941.0	5.996909e-01	4.900872e-01	0.0000	0.0000	1.00
Steel_Plate_Thickness	1941.0	7.873776e+01	5.508603e+01	40.0000	40.0000	7.00
Edges_Index	1941.0	3.317152e-01	2.997117e-01	0.0000	0.0604	2.2
Empty_Index	1941.0	4.142033e-01	1.372615e-01	0.0000	0.3158	4.1
Square_Index	1941.0	5.707671e-01	2.710584e-01	0.0083	0.3613	5.5
Outside_X_Index	1941.0	3.336110e-02	5.896117e-02	0.0015	0.0066	1.0
Edges_X_Index	1941.0	6.105286e-01	2.432769e-01	0.0144	0.4118	6.3
Edges_Y_Index	1941.0	8.134722e-01	2.342736e-01	0.0484	0.5968	9.4
Outside_Global_Index	1941.0	5.757342e-01	4.823520e-01	0.0000	0.0000	1.00
LogOfAreas	1941.0	2.492388e+00	7.889299e-01	0.3010	1.9243	2.24
Log_X_Index	1941.0	1.335686e+00	4.816116e-01	0.3010	1.0000	1.17
Log_Y_Index	1941.0	1.403271e+00	4.543452e-01	0.0000	1.0792	1.32
Orientation_Index	1941.0	8.328764e-02	5.008680e-01	-0.9910	-0.3333	9.5
Luminosity_Index	1941.0	-1.313050e-01	1.487668e-01	-0.9989	-0.1950	-1
SigmoidOfAreas	1941.0	5.854205e-01	3.394518e-01	0.1190	0.2482	5.0
Pastry	1941.0	8.140134e-02	2.735209e-01	0.0000	0.0000	0.00
Z_Scratch	1941.0	9.788769e-02	2.972393e-01	0.0000	0.0000	0.00
K_Scatch	1941.0	2.014426e-01	4.011812e-01	0.0000	0.0000	0.00
Stains	1941.0	3.709428e-02	1.890415e-01	0.0000	0.0000	0.00
Dirtiness	1941.0	2.833591e-02	1.659734e-01	0.0000	0.0000	0.00
Bumps	1941.0	2.071097e-01	4.053393e-01	0.0000	0.0000	0.00

	count	mean	std	min	25%
Other_Faults	1941.0	3.467285e-01	4.760510e-01	0.0000	0.0000 0.0(

In [288]:

```
df_steel.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1941 entries, 0 to 1940
Data columns (total 34 columns):
X_Minimum                1941 non-null int64
X_Maximum                1941 non-null int64
Y_Minimum                1941 non-null int64
Y_Maximum                1941 non-null int64
Pixels_Areas             1941 non-null int64
X_Perimeter              1941 non-null int64
Y_Perimeter              1941 non-null int64
Sum_of_Luminosity        1941 non-null int64
Minimum_of_Luminosity    1941 non-null int64
Maximum_of_Luminosity    1941 non-null int64
Length_of_Conveyer       1941 non-null int64
TypeOfSteel_A300         1941 non-null int64
TypeOfSteel_A400         1941 non-null int64
Steel_Plate_Thickness    1941 non-null int64
Edges_Index              1941 non-null float64
Empty_Index              1941 non-null float64
Square_Index             1941 non-null float64
Outside_X_Index          1941 non-null float64
Edges_X_Index            1941 non-null float64
Edges_Y_Index            1941 non-null float64
Outside_Global_Index     1941 non-null float64
LogOfAreas               1941 non-null float64
Log_X_Index              1941 non-null float64
Log_Y_Index              1941 non-null float64
Orientation_Index        1941 non-null float64
Luminosity_Index         1941 non-null float64
SigmoidOfAreas           1941 non-null float64
Pastry                   1941 non-null int64
Z_Scratch                1941 non-null int64
K_Scatch                 1941 non-null int64
Stains                   1941 non-null int64
Dirtiness                1941 non-null int64
Bumps                    1941 non-null int64
Other_Faults             1941 non-null int64
dtypes: float64(13), int64(21)
memory usage: 515.7 KB
```

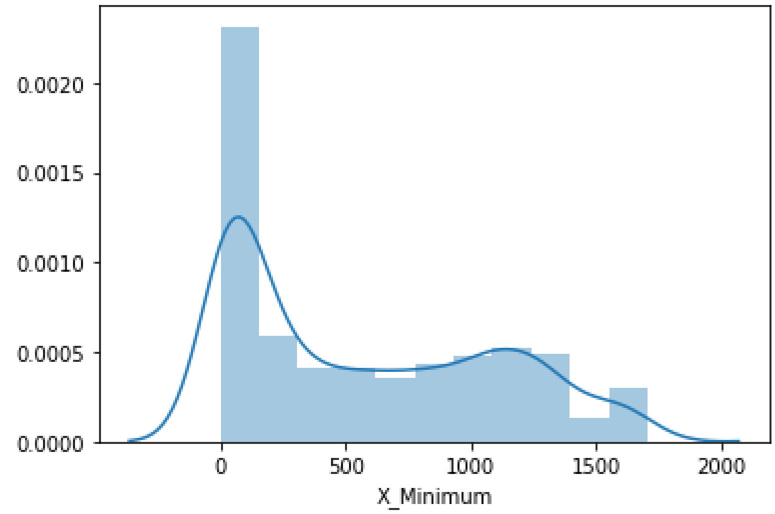
Missing value detection

In [289]:
```
#missing value detection
df_steel.isnull().sum()
```

Out[289]:
```
X_Minimum                0
X_Maximum                0
Y_Minimum                0
Y_Maximum                0
Pixels_Areas             0
X_Perimeter              0
Y_Perimeter              0
Sum_of_Luminosity        0
Minimum_of_Luminosity    0
Maximum_of_Luminosity    0
Length_of_Conveyer       0
TypeOfSteel_A300         0
TypeOfSteel_A400         0
Steel_Plate_Thickness    0
Edges_Index              0
Empty_Index              0
Square_Index             0
Outside_X_Index          0
Edges_X_Index            0
Edges_Y_Index            0
Outside_Global_Index     0
LogOfAreas               0
Log_X_Index              0
Log_Y_Index              0
Orientation_Index        0
Luminosity_Index         0
SigmoidOfAreas           0
Pastry                   0
Z_Scratch                0
K_Scatch                 0
Stains                   0
Dirtiness                0
Bumps                    0
Other_Faults             0
dtype: int64
```

In [290]:
```
sns.distplot(df_steel.X_Minimum )
```

Out[290]: <matplotlib.axes._subplots.AxesSubplot at 0x299b5d74f88>

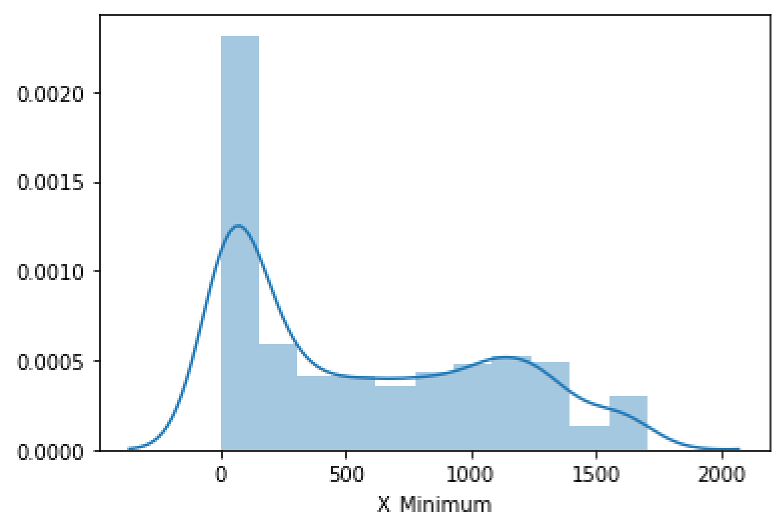


Plotting the histograms for all the variables to detect outliers and data distributions

In [291]:
```
for x in range(0, len(df_steel.columns)-8):
    print("Variable Name:" ,df_steel.columns[x])
    sns.distplot(df_steel.iloc[:,x])
    plt.show()
```

Variable Name: X_Minimum

Out[291]: <matplotlib.axes._subplots.AxesSubplot at 0x299b4f5ed08>

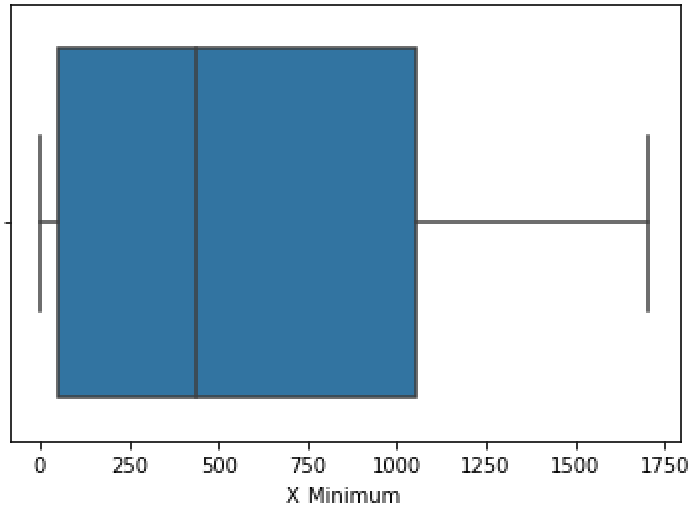


Boxplot for all the independent variables

In [292]:
```
for x in range(0, len(df_steel.columns)-8):
    print("Variable Name:" ,df_steel.columns[x])
    sns.boxplot(df_steel.iloc[:,x])
    plt.show()
```

Variable Name: X_Minimum

Out[292]: <matplotlib.axes._subplots.AxesSubplot at 0x299b5f2c388>

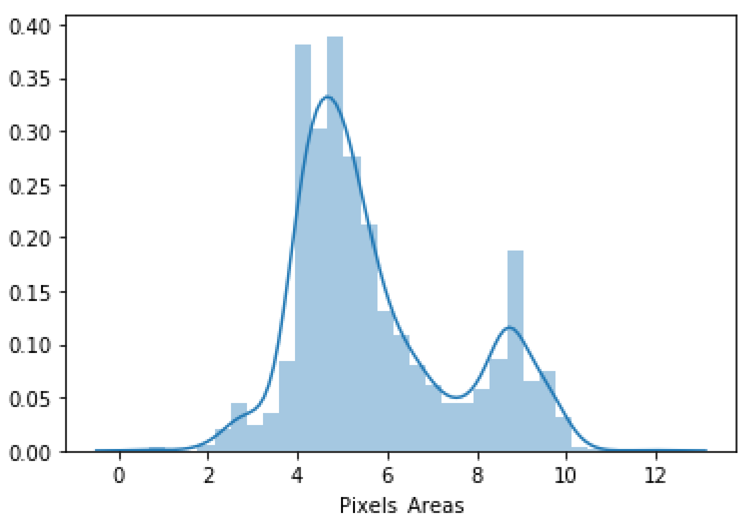


Log transforming the Pixel Areas variable

Observing a normal distribution after transforming the variables

In [293]:
```
sns.distplot(np.log(df_steel.Pixels_Areas))
```

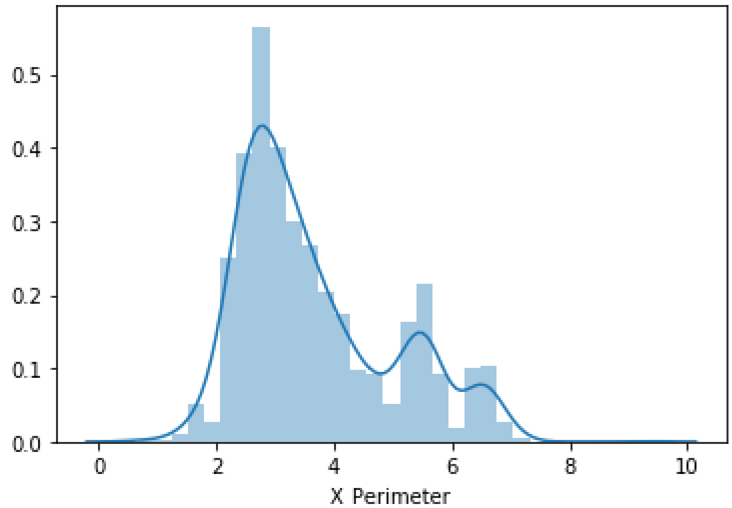
Out[293]: <matplotlib.axes._subplots.AxesSubplot at 0x299bf3e8908>



Observing a normal distribution after transforming the variables

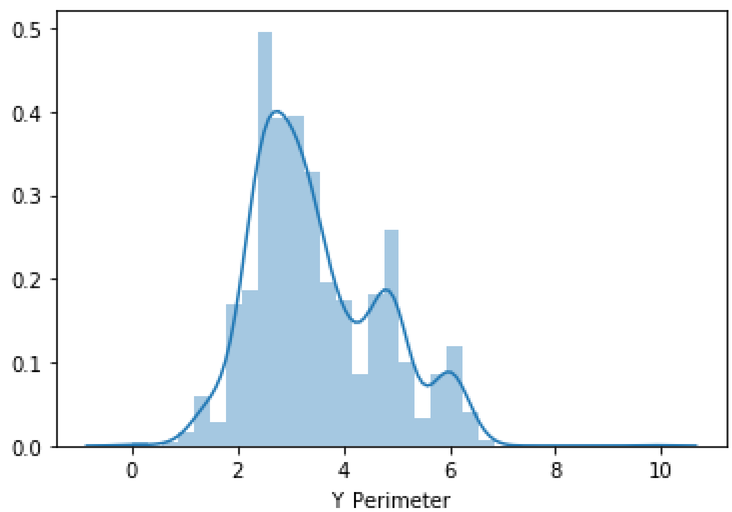
In [294]:
```
sns.distplot(np.log(df_steel.X_Perimeter))
```

Out[294]: <matplotlib.axes._subplots.AxesSubplot at 0x299b4f7f888>



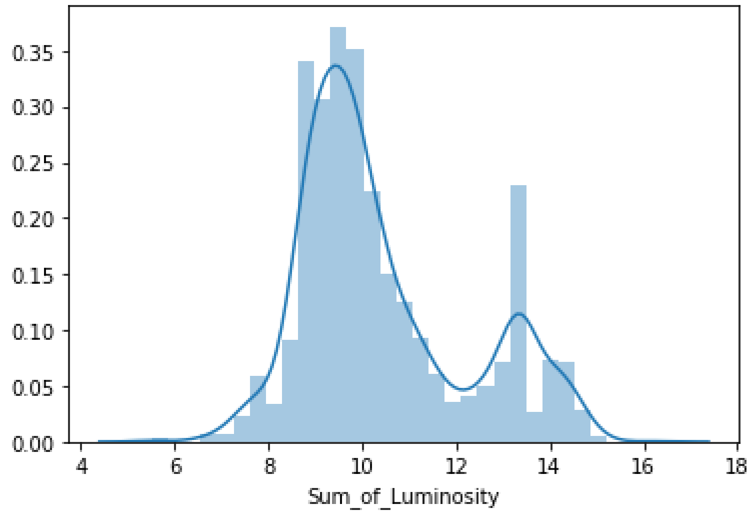
In [295]:
```
sns.distplot(np.log(df_steel.Y_Perimeter))
```

Out[295]: <matplotlib.axes._subplots.AxesSubplot at 0x299b798c3c8>



In [296]:
```
sns.distplot(np.log(df_steel.Sum_of_Luminosity))
```

Out[296]: <matplotlib.axes._subplots.AxesSubplot at 0x299b797a088>



Target variable - Defects distribution

In [297]:
```
df_steel[['Pastry', 'Z_Scratch', 'K_Scatch', 'Stains', 'Dirtiness', 'Bumps',
```

Out[297]:
```
Pastry          158
Z_Scratch       190
K_Scatch        391
Stains           72
Dirtiness        55
Bumps           402
Other_Faults    673
dtype: int64
```

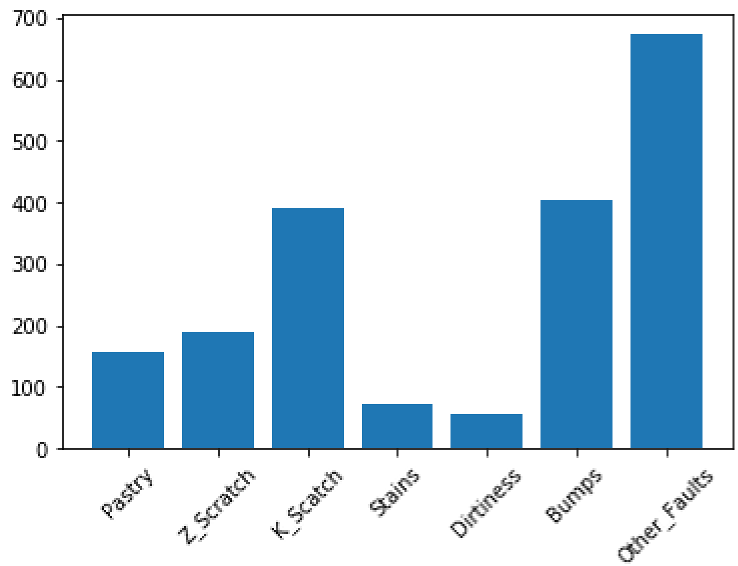
In [298]:
```
target_index = df_steel[['Pastry', 'Z_Scratch', 'K_Scatch', 'Stains', 'Dirtin
target_values = df_steel[['Pastry', 'Z_Scratch', 'K_Scatch', 'Stains', 'Dirti
```

distribution of the target variable

In [299]:
```
#distribution of the target variable
plt.bar(x=target_index, height= target_values)
plt.xticks(rotation=45)
```

Out[299]: `<BarContainer object of 7 artists>`

Out[299]: `([0, 1, 2, 3, 4, 5, 6], <a list of 7 Text xticklabel objects>)`



Clubbing the dummy coded target variable in 7 columns to one column

In [300]:
```
df_steel['Class']=0
```

In [301]:
```
df_steel['DefType']=''
```

In [302]:
```
#data Consolidation - Consolidating the target dummy variables into single va
df_steel.loc[df_steel.Pastry==1,'Class'] = 1
df_steel.loc[df_steel.Z_Scratch==1,'Class'] = 2
df_steel.loc[df_steel.K_Scatch==1,'Class'] = 3
df_steel.loc[df_steel.Stains==1,'Class'] = 4
df_steel.loc[df_steel.Dirtiness==1,'Class'] = 5
df_steel.loc[df_steel.Bumps==1,'Class'] = 6
df_steel.loc[df_steel.Other_Faults==1,'Class'] = 7
```

In [303]:
```
#data Consolidation - Consolidating the target dummy variables into single va
df_steel.loc[df_steel.Pastry==1,'DefType'] = 'Pastry'
df_steel.loc[df_steel.Z_Scratch==1,'DefType'] = 'Z_Scratch'
df_steel.loc[df_steel.K_Scatch==1,'DefType'] = 'K_Scatch'
df_steel.loc[df_steel.Stains==1,'DefType'] = 'Stains'
df_steel.loc[df_steel.Dirtiness==1,'DefType'] = 'Dirtiness'
df_steel.loc[df_steel.Bumps==1,'DefType'] = 'Bumps'
df_steel.loc[df_steel.Other_Faults==1,'DefType'] = 'Other_Faults'
```

In [304]:
```
df_steel.Class.value_counts()
```

Out[304]:
```
7    673
6    402
3    391
2    190
1    158
4     72
5     55
Name: Class, dtype: int64
```

In [305]:
```
df_steel[['Pastry', 'Z_Scratch', 'K_Scatch', 'Stains', 'Dirtiness', 'Bumps',
```

Out[305]:
```
Pastry          158
Z_Scratch       190
K_Scatch        391
Stains           72
Dirtiness        55
Bumps           402
Other_Faults    673
dtype: int64
```

In [306]:
```
df_steel[['Class','DefType']].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1941 entries, 0 to 1940
Data columns (total 2 columns):
Class      1941 non-null int64
DefType    1941 non-null object
dtypes: int64(1), object(1)
memory usage: 30.5+ KB
```

In [307]:
```
df_steel['Class'] = df_steel['Class'].astype('int64')
```

In [308]:
```
df_steel[['Class','DefType']].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1941 entries, 0 to 1940
Data columns (total 2 columns):
Class      1941 non-null int64
DefType    1941 non-null object
dtypes: int64(1), object(1)
memory usage: 30.5+ KB
```

Removing the dummy coded target variables

In [309]:
```
df =df_steel.loc[:, ~df_steel.columns.isin(['Pastry', 'Z_Scratch', 'K_Scatch'
```

In [310]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1941 entries, 0 to 1940
Data columns (total 29 columns):
X_Minimum                1941 non-null int64
X_Maximum                1941 non-null int64
Y_Minimum                1941 non-null int64
Y_Maximum                1941 non-null int64
Pixels_Areas             1941 non-null int64
X_Perimeter              1941 non-null int64
Y_Perimeter              1941 non-null int64
Sum_of_Luminosity        1941 non-null int64
Minimum_of_Luminosity    1941 non-null int64
Maximum_of_Luminosity    1941 non-null int64
Length_of_Conveyer       1941 non-null int64
TypeOfSteel_A300         1941 non-null int64
TypeOfSteel_A400         1941 non-null int64
Steel_Plate_Thickness    1941 non-null int64
Edges_Index              1941 non-null float64
Empty_Index              1941 non-null float64
Square_Index             1941 non-null float64
Outside_X_Index          1941 non-null float64
Edges_X_Index            1941 non-null float64
Edges_Y_Index            1941 non-null float64
Outside_Global_Index     1941 non-null float64
LogOfAreas               1941 non-null float64
Log_X_Index              1941 non-null float64
Log_Y_Index              1941 non-null float64
Orientation_Index        1941 non-null float64
Luminosity_Index         1941 non-null float64
SigmoidOfAreas           1941 non-null float64
Class                    1941 non-null int64
DefType                  1941 non-null object
dtypes: float64(13), int64(15), object(1)
memory usage: 439.9+ KB
```

In [311]:
```
df.DefType.value_counts()
```

Out[311]:
```
Other_Faults    673
Bumps           402
K_Scatch        391
Z_Scratch       190
Pastry          158
Stains           72
Dirtiness        55
Name: DefType, dtype: int64
```

In [312]:
```
df.Class.value_counts()
```

Out[312]:
```
7    673
6    402
3    391
2    190
1    158
4     72
5     55
Name: Class, dtype: int64
```

In [313]:
```
#df.to_csv("Faulty_Steel_Plates.CSV",index=False)
```

In [314]:

```
df.describe().T
```

Out[314]:

	count	mean	std	min	25%	
X_Minimum	1941.0	5.711360e+02	5.206907e+02	0.0000	51.0000	4.35000
X_Maximum	1941.0	6.179645e+02	4.976274e+02	4.0000	192.0000	4.67000
Y_Minimum	1941.0	1.650685e+06	1.774578e+06	6712.0000	471253.0000	1.20412
Y_Maximum	1941.0	1.650739e+06	1.774590e+06	6724.0000	471281.0000	1.20413
Pixels_Areas	1941.0	1.893878e+03	5.168460e+03	2.0000	84.0000	1.74000
X_Perimeter	1941.0	1.118552e+02	3.012092e+02	2.0000	15.0000	2.60000
Y_Perimeter	1941.0	8.296600e+01	4.264829e+02	1.0000	13.0000	2.50000
Sum_of_Luminosity	1941.0	2.063121e+05	5.122936e+05	250.0000	9522.0000	1.92020
Minimum_of_Luminosity	1941.0	8.454869e+01	3.213428e+01	0.0000	63.0000	9.00000
Maximum_of_Luminosity	1941.0	1.301937e+02	1.869099e+01	37.0000	124.0000	1.27000
Length_of_Conveyer	1941.0	1.459160e+03	1.445778e+02	1227.0000	1358.0000	1.36400
TypeOfSteel_A300	1941.0	4.003091e-01	4.900872e-01	0.0000	0.0000	0.00000
TypeOfSteel_A400	1941.0	5.996909e-01	4.900872e-01	0.0000	0.0000	1.00000
Steel_Plate_Thickness	1941.0	7.873776e+01	5.508603e+01	40.0000	40.0000	7.00000
Edges_Index	1941.0	3.317152e-01	2.997117e-01	0.0000	0.0604	2.27300
Empty_Index	1941.0	4.142033e-01	1.372615e-01	0.0000	0.3158	4.12100
Square_Index	1941.0	5.707671e-01	2.710584e-01	0.0083	0.3613	5.55600
Outside_X_Index	1941.0	3.336110e-02	5.896117e-02	0.0015	0.0066	1.01000
Edges_X_Index	1941.0	6.105286e-01	2.432769e-01	0.0144	0.4118	6.36400
Edges_Y_Index	1941.0	8.134722e-01	2.342736e-01	0.0484	0.5968	9.47400
Outside_Global_Index	1941.0	5.757342e-01	4.823520e-01	0.0000	0.0000	1.00000
LogOfAreas	1941.0	2.492388e+00	7.889299e-01	0.3010	1.9243	2.24060
Log_X_Index	1941.0	1.335686e+00	4.816116e-01	0.3010	1.0000	1.17610
Log_Y_Index	1941.0	1.403271e+00	4.543452e-01	0.0000	1.0792	1.32220
Orientation_Index	1941.0	8.328764e-02	5.008680e-01	-0.9910	-0.3333	9.52000
Luminosity_Index	1941.0	-1.313050e-01	1.487668e-01	-0.9989	-0.1950	-1.330
SigmoidOfAreas	1941.0	5.854205e-01	3.394518e-01	0.1190	0.2482	5.06300
Class	1941.0	4.841319e+00	2.144175e+00	1.0000	3.0000	6.00000

Corelation

In [315]:

```
df.corr()
```

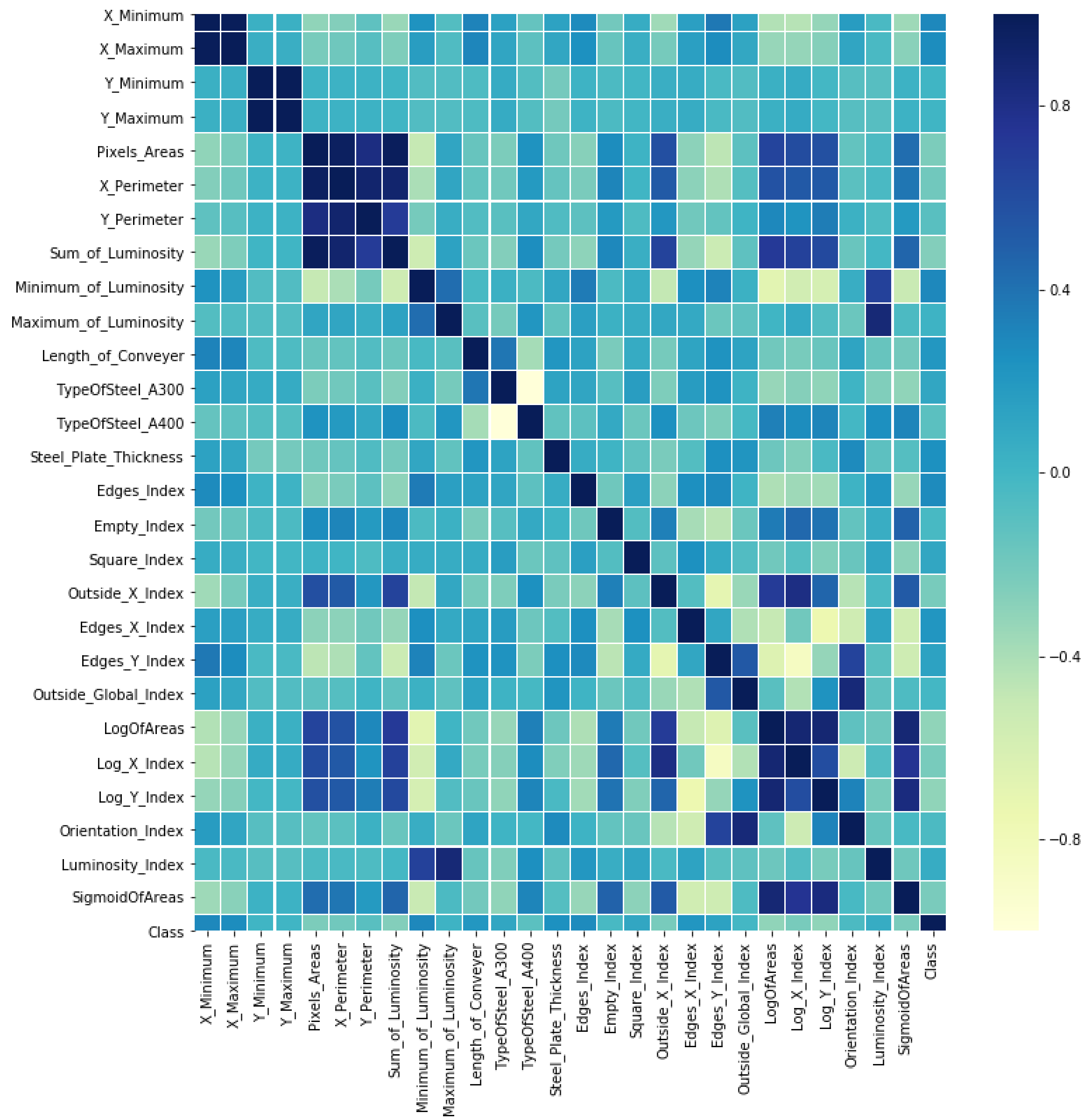
Out[315]:

	X_Minimum	X_Maximum	Y_Minimum	Y_Maximum	Pixels_Areas	X_
X_Minimum	1.000000	0.988314	0.041821	0.041807	-0.307322	
X_Maximum	0.988314	1.000000	0.052147	0.052135	-0.225399	
Y_Minimum	0.041821	0.052147	1.000000	1.000000	0.017670	
Y_Maximum	0.041807	0.052135	1.000000	1.000000	0.017840	
Pixels_Areas	-0.307322	-0.225399	0.017670	0.017840	1.000000	
X_Perimeter	-0.258937	-0.186326	0.023843	0.024038	0.966644	
Y_Perimeter	-0.118757	-0.090138	0.024150	0.024380	0.827199	
Sum_of_Luminosity	-0.339045	-0.247052	0.007362	0.007499	0.978952	
Minimum_of_Luminosity	0.237637	0.168649	-0.065703	-0.065733	-0.497204	
Maximum_of_Luminosity	-0.075554	-0.062392	-0.067785	-0.067776	0.110063	
Length_of_Conveyer	0.316662	0.299390	-0.049211	-0.049219	-0.155853	
TypeOfSteel_A300	0.144319	0.112009	0.075164	0.075151	-0.235591	
TypeOfSteel_A400	-0.144319	-0.112009	-0.075164	-0.075151	0.235591	
Steel_Plate_Thickness	0.136625	0.106119	-0.207640	-0.207644	-0.183735	
Edges_Index	0.278075	0.242846	0.021314	0.021300	-0.275289	
Empty_Index	-0.198461	-0.152680	-0.043117	-0.043085	0.272808	
Square_Index	0.063658	0.048575	-0.006135	-0.006152	0.017865	
Outside_X_Index	-0.361160	-0.214930	0.054165	0.054185	0.588606	
Edges_X_Index	0.154778	0.149259	0.066085	0.066051	-0.294673	
Edges_Y_Index	0.367907	0.271915	-0.036543	-0.036549	-0.463571	
Outside_Global_Index	0.147282	0.099253	-0.062911	-0.062901	-0.109655	
LogOfAreas	-0.428553	-0.332169	0.044952	0.044994	0.650234	
Log_X_Index	-0.437944	-0.324012	0.070406	0.070432	0.603072	
Log_Y_Index	-0.326851	-0.265990	-0.008442	-0.008382	0.578342	
Orientation_Index	0.178585	0.115019	-0.086497	-0.086480	-0.137604	
Luminosity_Index	-0.031578	-0.038996	-0.090654	-0.090666	-0.043449	
SigmoidOfAreas	-0.355251	-0.286736	0.025257	0.025284	0.422947	
Class	0.291760	0.269444	0.000106	0.000093	-0.239093	

Corelation Plot

In [316]:
```
corrmat = df.corr()
f, ax = plt.subplots(figsize=(12,12))
sns.heatmap(corrmat,ax=ax,cmap="YlGnBu",linewidths =0.1)
```

Out[316]: <matplotlib.axes._subplots.AxesSubplot at 0x299bec752c8>



Predictive Modelling with all Unchanged independent variables

Splitting the data into training and testing

In [317]:
```
#shuffling the data
#df = df.sample(frac=1).reset_index(drop=True)
print(df.shape)
```

```
(1941, 29)
```

In [318]:
```
X_parts = df.loc[ :, ~df.columns.isin(['Class','DefType'])]
X_parts.head()
print(X_parts.shape)
```

Out[318]:

	X_Minimum	X_Maximum	Y_Minimum	Y_Maximum	Pixels_Areas	X_Perimeter	Y_Perimeter
0	42	50	270900	270944	267	17	44
1	645	651	2538079	2538108	108	10	30
2	829	835	1553913	1553931	71	8	19
3	853	860	369370	369415	176	13	45
4	1289	1306	498078	498335	2409	60	260

```
(1941, 27)
```

In [319]:
```
Y_cat = df.loc[:, 'DefType']
print(len(Y_cat.unique()))
Y_cat.head()
```

```
7
```

Out[319]:
```
0    Pastry
1    Pastry
2    Pastry
3    Pastry
4    Pastry
Name: DefType, dtype: object
```

In [320]:
```
X_train, X_test, y_train, y_test = train_test_split(X_parts, Y_cat, test_size
```

In [321]:
```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(1358, 27)
(583, 27)
(1358,)
(583,)
```

In [322]:

```
X_train.describe().T
```

Out[322]:

	count	mean	std	min	25%	
X_Minimum	1358.0	5.726635e+02	5.244790e+02	0.0000	48.000000	4.190
X_Maximum	1358.0	6.183660e+02	5.016641e+02	4.0000	191.250000	4.595
Y_Minimum	1358.0	1.678222e+06	1.736243e+06	6712.0000	492998.250000	1.229
Y_Maximum	1358.0	1.678265e+06	1.736242e+06	6724.0000	493105.750000	1.229
Pixels_Areas	1358.0	1.781730e+03	3.851907e+03	2.0000	82.000000	1.670
X_Perimeter	1358.0	1.036701e+02	1.836486e+02	2.0000	14.000000	2.500
Y_Perimeter	1358.0	7.181885e+01	1.142033e+02	1.0000	13.000000	2.400
Sum_of_Luminosity	1358.0	1.963177e+05	4.395054e+05	250.0000	9210.250000	1.851
Minimum_of_Luminosity	1358.0	8.456554e+01	3.216052e+01	0.0000	63.000000	9.000
Maximum_of_Luminosity	1358.0	1.299514e+02	1.837353e+01	37.0000	124.000000	1.270
Length_of_Conveyer	1358.0	1.459236e+03	1.446490e+02	1227.0000	1358.000000	1.364
TypeOfSteel_A300	1358.0	4.057437e-01	4.912163e-01	0.0000	0.000000	0.000
TypeOfSteel_A400	1358.0	5.942563e-01	4.912163e-01	0.0000	0.000000	1.000
Steel_Plate_Thickness	1358.0	7.848012e+01	5.430125e+01	40.0000	40.000000	7.000
Edges_Index	1358.0	3.287971e-01	3.003263e-01	0.0000	0.060400	2.216
Empty_Index	1358.0	4.131761e-01	1.333801e-01	0.0000	0.321400	4.092
Square_Index	1358.0	5.703882e-01	2.707642e-01	0.0090	0.360875	5.556
Outside_X_Index	1358.0	3.256870e-02	5.522742e-02	0.0015	0.006600	9.600
Edges_X_Index	1358.0	6.157730e-01	2.418829e-01	0.0657	0.428600	6.429
Edges_Y_Index	1358.0	8.142315e-01	2.341229e-01	0.0484	0.597175	9.491
Outside_Global_Index	1358.0	5.636966e-01	4.842701e-01	0.0000	0.000000	1.000
LogOfAreas	1358.0	2.476850e+00	7.853281e-01	0.3010	1.913800	2.222
Log_X_Index	1358.0	1.328766e+00	4.798089e-01	0.3010	1.000000	1.146
Log_Y_Index	1358.0	1.392601e+00	4.474672e-01	0.0000	1.079200	1.322
Orientation_Index	1358.0	7.896510e-02	5.017729e-01	-0.9910	-0.333300	9.090
Luminosity_Index	1358.0	-1.324339e-01	1.512378e-01	-0.9989	-0.193225	-1.3
SigmoidOfAreas	1358.0	5.760945e-01	3.389218e-01	0.1190	0.243200	4.763

In [323]:

```
X_test.describe().T
```

Out[323]:

	count	mean	std	min	25%	
X_Minimum	583.0	5.675780e+02	5.121860e+02	0.0000	67.50000	4.57000
X_Maximum	583.0	6.170292e+02	4.885201e+02	8.0000	194.50000	4.93000
Y_Minimum	583.0	1.586543e+06	1.860767e+06	7003.0000	410706.00000	1.10535
Y_Maximum	583.0	1.586621e+06	1.860808e+06	7020.0000	410830.00000	1.10538
Pixels_Areas	583.0	2.155108e+03	7.372309e+03	6.0000	90.50000	1.94000
X_Perimeter	583.0	1.309211e+02	4.725091e+02	4.0000	16.00000	2.90000
Y_Perimeter	583.0	1.089314e+02	7.582328e+02	2.0000	14.00000	2.60000
Sum_of_Luminosity	583.0	2.295924e+05	6.508866e+05	775.0000	10691.00000	2.12160
Minimum_of_Luminosity	583.0	8.450943e+01	3.210062e+01	0.0000	63.50000	8.90000
Maximum_of_Luminosity	583.0	1.307581e+02	1.941476e+01	84.0000	124.00000	1.27000
Length_of_Conveyer	583.0	1.458985e+03	1.445360e+02	1227.0000	1358.00000	1.36400
TypeOfSteel_A300	583.0	3.876501e-01	4.876324e-01	0.0000	0.00000	0.00000
TypeOfSteel_A400	583.0	6.123499e-01	4.876324e-01	0.0000	0.00000	1.00000
Steel_Plate_Thickness	583.0	7.933791e+01	5.691509e+01	40.0000	40.00000	7.00000
Edges_Index	583.0	3.385123e-01	2.984216e-01	0.0000	0.06040	2.4080
Empty_Index	583.0	4.165962e-01	1.459938e-01	0.0278	0.30270	4.1670
Square_Index	583.0	5.716497e-01	2.719732e-01	0.0083	0.36335	5.5800
Outside_X_Index	583.0	3.520686e-02	6.687004e-02	0.0022	0.00660	1.0400
Edges_X_Index	583.0	5.983127e-01	2.462695e-01	0.0144	0.39340	6.1910
Edges_Y_Index	583.0	8.117036e-01	2.348160e-01	0.1123	0.59355	9.4740
Outside_Global_Index	583.0	6.037736e-01	4.770897e-01	0.0000	0.00000	1.00000
LogOfAreas	583.0	2.528583e+00	7.967589e-01	0.7782	1.95660	2.28780
Log_X_Index	583.0	1.351806e+00	4.858160e-01	0.4771	1.00000	1.17610
Log_Y_Index	583.0	1.428127e+00	4.694271e-01	0.3010	1.07920	1.36170
Orientation_Index	583.0	9.335626e-02	4.990385e-01	-0.9739	-0.29410	1.1310
Luminosity_Index	583.0	-1.286756e-01	1.429379e-01	-0.5678	-0.19850	-1.33
SigmoidOfAreas	583.0	6.071437e-01	3.399826e-01	0.1262	0.25830	5.4610

In [324]:
```
y_train.value_counts()
```

Out[324]:
```
Other_Faults    462
Bumps           287
K_Scatch        268
Z_Scratch       132
Pastry          120
Stains           49
Dirtiness        40
Name: DefType, dtype: int64
```

In [325]:
```
y_test.value_counts()
```

Out[325]:
```
Other_Faults    211
K_Scatch        123
Bumps           115
Z_Scratch        58
Pastry           38
Stains           23
Dirtiness        15
Name: DefType, dtype: int64
```

Decision Trees

In [326]:
```
col_names = list(df.loc[ :, ~df.columns.isin(['Class','DefType'])].columns.va
classnames = list(df.DefType.unique())
```

In [327]:
```
##Performing Descision trees using all categories
tre2 = tree.DecisionTreeClassifier().fit(X_train,y_train)

predicted = tre2.predict(X_test)

print(metrics.classification_report(y_test, predicted))
```

```
              precision    recall  f1-score   support

       Bumps       0.63      0.51      0.57       115
   Dirtiness       0.67      0.67      0.67        15
    K_Scatch       0.87      0.90      0.88       123
Other_Faults       0.64      0.62      0.63       211
      Pastry       0.34      0.53      0.41        38
      Stains       0.96      0.96      0.96        23
   Z_Scratch       0.79      0.86      0.83        58

    accuracy                           0.69       583
   macro avg       0.70      0.72      0.71       583
weighted avg       0.70      0.69      0.69       583
```

Confusion Matrix of Predicted vs Actual - Test Data

In [328]:
```
cm = metrics.confusion_matrix(y_test, predicted)
print(cm)
```

```
[[ 59   0   2  39  12   0   3]
 [  1  10   0   3   1   0   0]
 [  0   0 111  11   0   0   1]
 [ 26   5  15 130  25   1   9]
 [  6   0   0  12  20   0   0]
 [  0   0   0   1   0  22   0]
 [  1   0   0   6   1   0  50]]
```

In [329]:
```
#cm chart
plt.matshow(cm)
plt.title('Confusion Matrix')
plt.xlabel('Actual Value')
plt.ylabel('Predicted Value')
plt.xticks([0,1,2,3,4,5,6], ['I','II','III','IV','V','VI','VII'])
```

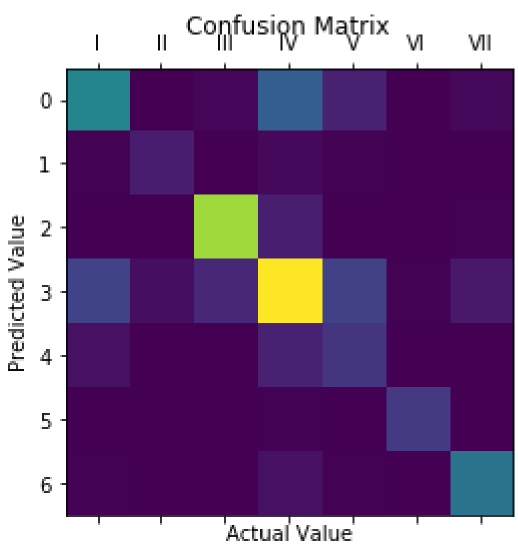
Out[329]:
```
<matplotlib.image.AxesImage at 0x299bd522d88>
```

Out[329]:
```
Text(0.5, 1.05, 'Confusion Matrix')
```

Out[329]:
```
Text(0.5, 0, 'Actual Value')
```

Out[329]:
```
Text(0, 0.5, 'Predicted Value')
```

Out[329]:
```
([<matplotlib.axis.XTick at 0x299bf03d3c8>,
  <matplotlib.axis.XTick at 0x299bf251348>,
  <matplotlib.axis.XTick at 0x299bd522fc8>,
  <matplotlib.axis.XTick at 0x299bd51f148>,
  <matplotlib.axis.XTick at 0x299bd51f808>,
  <matplotlib.axis.XTick at 0x299bd519ec8>,
  <matplotlib.axis.XTick at 0x299bd519048>],
 <a list of 7 Text xticklabel objects>)
```



Important Features in the decision tree model

In [330]:
```
eli5.show_weights(tre2,feature_names = list(X_test.columns),top=None)
```

Out[330]:

Weight	Feature
0.1883	Log_X_Index
0.0763	Length_of_Conveyer
0.0675	Steel_Plate_Thickness
0.0578	Maximum_of_Luminosity
0.0542	TypeOfSteel_A400
0.0532	Pixels_Areas
0.0501	Square_Index
0.0422	Y_Minimum
0.0402	Edges_Index
0.0389	Edges_Y_Index
0.0327	Edges_X_Index
0.0313	Y_Maximum
0.0313	X_Maximum
0.0299	Log_Y_Index
0.0298	X_Minimum
0.0265	Minimum_of_Luminosity
0.0263	TypeOfSteel_A300
0.0231	Sum_of_Luminosity
0.0207	Empty_Index
0.0202	X_Perimeter
0.0142	Orientation_Index
0.0101	Y_Perimeter
0.0090	Outside_X_Index

Interpreting which variables are impacting in predicting an observation

In [331]:
```
print("Actual defect value is:",y_test.iloc[150])
test_row = pd.DataFrame(X_test.iloc[150,:]).T
```

```
Actual defect value is: Other_Faults
```

Contribution of feature in predicting the category

In [332]:

```
#eli5.show_prediction(tre2, test_row.values[0],feature_names=list(X_test.colu
lid = [150]
for i in lid:
    print("Actual test value:",y_test.iloc[i])
    print("------------")
    print("Pedidcted value is ")

eli5.show_prediction(tre2, X_test.iloc[i], feature_names = list(X_train.colum
```

```
Actual test value: Other_Faults
------------
Pedidcted value is
```

Out[332]:

y=Bumps (probability **0.000**) top features		**y=Dirtiness** (probability **0.000**) top features		**y=K_Scatch** (probability features	
Contribution?	**Feature**	**Contribution?**	**Feature**	**Contribution?**	**Feature**
+0.211	<BIAS>	+0.044	Square_Index	+0.197	<BIAS>
+0.043	Log_X_Index	+0.029	<BIAS>	+0.008	Edges_Y
+0.015	Outside_X_Index	+0.006	Log_X_Index	+0.006	Outside_
+0.011	Pixels_Areas	+0.002	Pixels_Areas	+0.002	Y_Minim
-0.002	Y_Minimum	-0.003	Length_of_Conveyer	+0.000	Sum_of_
-0.016	Sum_of_Luminosity	-0.035	Edges_Y_Index	+0.000	Pixels_A
-0.030	Edges_Y_Index	-0.043	Y_Minimum	-0.017	Length_(
-0.063	Length_of_Conveyer			-0.027	Square_
-0.169	Square_Index			-0.170	Log_X_I

Decision Tree rules

In [333]:

```
from sklearn.tree import _tree

def tree_to_pseudo(tree, feature_names):

    left = tree.tree_.children_left
    right = tree.tree_.children_right
    threshold = tree.tree_.threshold
    features = [feature_names[i] for i in tree.tree_.feature]
    value = tree.tree_.value

    def recurse(left, right, threshold, features, node, depth=0):
        indent = "  " * depth
        if (threshold[node] != -2):
            print (indent,"if ( " + features[node] + " <= " + str(threshold[r
            if left[node] != -1:
                recurse (left, right, threshold, features, left[node], depth+
                print (indent,"} else {")
                if right[node] != -1:
                    recurse (left, right, threshold, features, right[node], c
                print (indent,"}")
        else:
            print (indent,"return " + str(value[node]))

    recurse(left, right, threshold, features, 0)
tree_to_pseudo(tre2, list(X_train.columns))
```

```
 if ( Log_X_Index <= 2.0588001012802124 ) {
   if ( Pixels_Areas <= 30.0 ) {
     if ( Steel_Plate_Thickness <= 75.0 ) {
       if ( Steel_Plate_Thickness <= 45.0 ) {
         return [[0. 0. 2. 0. 0. 0. 0.]]
       } else {
         return [[ 0.   0.   0.   0.   0. 43.   0.]]
       }
     } else {
       if ( Square_Index <= 0.9000000059604645 ) {
         return [[0. 0. 0. 4. 0. 0. 0.]]
       } else {
         return [[1. 0. 0. 0. 0. 0. 0.]]
       }
     }
   } else {
     if ( Square_Index <= 0.5042499899864197 ) {
       if ( Edges_Y_Index <= 0.9775499999523163 ) {
         if ( Length_of_Conveyer <= 1359.0 ) {
```

node rules- in text format

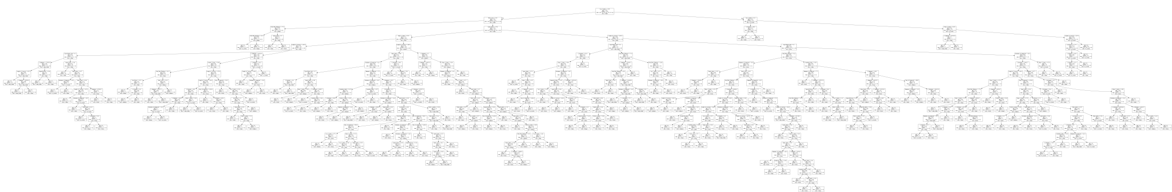
In [334]:

```
dotfile = open(r"C:\Users\Anirud Vem\Desktop\Faulty steel plates\dt_rules.dot
tree.export_graphviz(tre2, out_file=dotfile, feature_names=list(X_train.colum
dotfile.close()
```

In [335]:

```
# Load Libraries
from sklearn.tree import DecisionTreeClassifier
from sklearn import datasets
from IPython.display import Image
from sklearn import tree
import pydotplus

col_names = list(df.loc[ :, ~df.columns.isin(['Class','DefType'])].columns.va
classnames = list(df.DefType.unique())

# Create DOT data
dot_data = tree.export_graphviz(tre2, out_file=None,
                                feature_names=col_names,
                                class_names=classnames)

# Draw graph
graph = pydotplus.graph_from_dot_data(dot_data)

# Show graph
Image(graph.create_png())

# Create PDF
#graph.write_pdf("faultyplates.pdf")

# Create PNG
graph.write_png("faultyplates.png")
```

Out[335]:



Out[335]: True

Building Random Forest Model

In [336]:

```
##Performing random forest using all categories
from sklearn.ensemble import RandomForestClassifier
rand1 = RandomForestClassifier().fit(X_train,y_train)

rand1_pred = rand1.predict(X_test)

print(metrics.classification_report(y_test, rand1_pred))
```

```
              precision    recall  f1-score   support

       Bumps       0.58      0.65      0.61       115
   Dirtiness       0.81      0.87      0.84        15
    K_Scatch       0.96      0.92      0.94       123
Other_Faults       0.69      0.68      0.68       211
      Pastry       0.50      0.50      0.50        38
      Stains       1.00      0.91      0.95        23
   Z_Scratch       0.92      0.81      0.86        58

    accuracy                           0.74       583
   macro avg       0.78      0.76      0.77       583
weighted avg       0.75      0.74      0.74       583


C:\ProgramData\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:245:
FutureWarning: The default value of n_estimators will change from 10 in ver
sion 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

Confusion matrix on random forest

In [337]:

```
cm = metrics.confusion_matrix(y_test, rand1_pred)
print(cm)
```

```
[[ 75   0   1  33   6   0   0]
 [  0  13   0   1   1   0   0]
 [  1   0 113   9   0   0   0]
 [ 45   3   3 144  12   0   4]
 [  8   0   0  11  19   0   0]
 [  0   0   0   2   0  21   0]
 [  0   0   1  10   0   0  47]]
```

In [338]:

```
#cm chart
plt.matshow(cm)
plt.title('Confusion Matrix')
plt.xlabel('Actual Value')
plt.ylabel('Predicted Value')
plt.xticks([0,1,2,3,4,5,6], ['I','II','III','IV','V','VI','VII'])
```

Out[338]:

```
<matplotlib.image.AxesImage at 0x299b667e3c8>
```

Out[338]:

```
Text(0.5, 1.05, 'Confusion Matrix')
```

Out[338]:

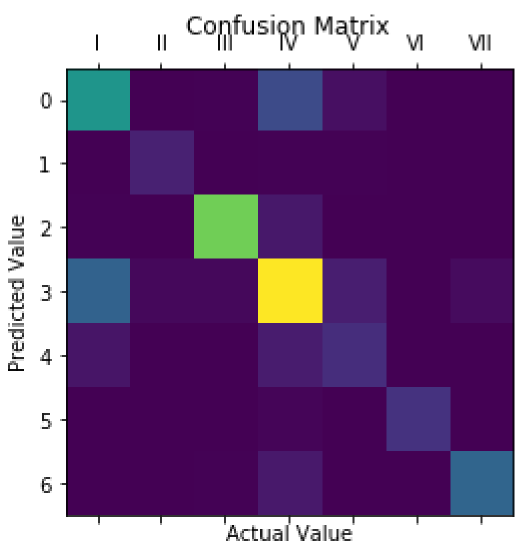
```
Text(0.5, 0, 'Actual Value')
```

Out[338]:

```
Text(0, 0.5, 'Predicted Value')
```

Out[338]:

```
([<matplotlib.axis.XTick at 0x299b3b91108>,
  <matplotlib.axis.XTick at 0x299be9a9948>,
  <matplotlib.axis.XTick at 0x299c28ab288>,
  <matplotlib.axis.XTick at 0x299c25fbb48>,
  <matplotlib.axis.XTick at 0x299c2748208>,
  <matplotlib.axis.XTick at 0x299c28637c8>,
  <matplotlib.axis.XTick at 0x299c28cda48>],
 <a list of 7 Text xticklabel objects>)
```



Feature Importance

In [339]:
```
eli5.show_weights(rand1,feature_names=list(X_test.columns),top=None)
```

Out[339]:

Weight	Feature
0.0846 ± 0.1850	Pixels_Areas
0.0698 ± 0.0473	Length_of_Conveyer
0.0651 ± 0.1234	X_Perimeter
0.0575 ± 0.1014	Steel_Plate_Thickness
0.0540 ± 0.1499	Log_X_Index
0.0487 ± 0.0827	Minimum_of_Luminosity
0.0481 ± 0.0589	X_Minimum
0.0433 ± 0.0295	X_Maximum
0.0412 ± 0.0726	Edges_Y_Index
0.0400 ± 0.0284	Square_Index
0.0398 ± 0.0147	Y_Minimum
0.0373 ± 0.0412	Sum_of_Luminosity
0.0370 ± 0.0200	Luminosity_Index
0.0358 ± 0.0276	Orientation_Index
0.0339 ± 0.0261	Y_Maximum
0.0320 ± 0.0242	Edges_Index
0.0298 ± 0.0157	Empty_Index
0.0257 ± 0.0264	SigmoidOfAreas
0.0250 ± 0.0149	Maximum_of_Luminosity
0.0249 ± 0.0386	LogOfAreas
0.0243 ± 0.0250	Outside_X_Index
0.0219 ± 0.0321	TypeOfSteel_A300
0.0218 ± 0.0247	Edges_X_Index
0.0194 ± 0.0190	Y_Perimeter
0.0178 ± 0.0083	Log_Y_Index
0.0175 ± 0.0262	TypeOfSteel_A400
0.0037 ± 0.0042	Outside_Global_Index

Neural Network

In [340]:
```
# Standardize the scaling of the variables by
# computing the mean and std to be used for later scaling.
scaler = preprocessing.StandardScaler()
scaler.fit(X_train)

# Perform the standardization process
steel_data_train_std = scaler.transform(X_train)
steel_data_test_std = scaler.transform(X_test)
```

Out[340]:
```
StandardScaler(copy=True, with_mean=True, with_std=True)
```

In [341]:

```
nnclass2 = MLPClassifier(activation='relu', solver='sgd',
                         hidden_layer_sizes=(50,50,50))
nnclass2.fit(steel_data_train_std, y_train)

nnclass2_pred = nnclass2.predict(steel_data_test_std)

print(metrics.classification_report(y_test, nnclass2_pred))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neural_network\multilaye
r_perceptron.py:566: ConvergenceWarning: Stochastic Optimizer: Maximum iter
ations (200) reached and the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
```

Out[341]:

```
MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.
9,
              beta_2=0.999, early_stopping=False, epsilon=1e-08,
              hidden_layer_sizes=(50, 50, 50), learning_rate='constant',
              learning_rate_init=0.001, max_iter=200, momentum=0.9,
              n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5,
              random_state=None, shuffle=True, solver='sgd', tol=0.0001,
              validation_fraction=0.1, verbose=False, warm_start=False)
```

```
              precision    recall  f1-score   support

       Bumps       0.55      0.58      0.57       115
   Dirtiness       1.00      0.20      0.33        15
    K_Scatch       0.95      0.93      0.94       123
Other_Faults       0.66      0.66      0.66       211
      Pastry       0.43      0.53      0.48        38
      Stains       0.90      0.83      0.86        23
   Z_Scratch       0.85      0.88      0.86        58

    accuracy                           0.71       583
   macro avg       0.76      0.66      0.67       583
weighted avg       0.72      0.71      0.71       583
```

In [342]:

```
cm = metrics.confusion_matrix(y_test, nnclass2_pred)
print(cm)
```

```
[[ 67   0   1  40   4   0   3]
 [  1   3   0   5   6   0   0]
 [  0   0 114   9   0   0   0]
 [ 44   0   5 140  16   2   4]
 [  6   0   0  10  20   0   2]
 [  1   0   0   3   0  19   0]
 [  2   0   0   5   0   0  51]]
```

In [343]:
```
plt.matshow(cm)
plt.title('Confusion Matrix')
plt.xlabel('Actual Value')
plt.ylabel('Predicted Value')
plt.xticks([0,1,2,3,4,5,6], ['I','II','III','IV','V','VI','VII'])
```

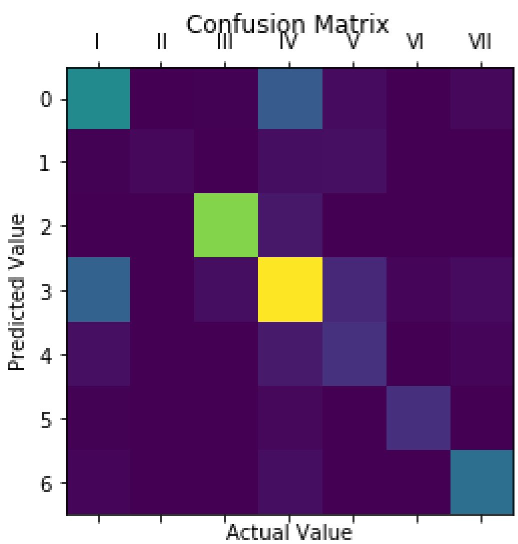
Out[343]:
```
<matplotlib.image.AxesImage at 0x299c28dff48>
```

Out[343]:
```
Text(0.5, 1.05, 'Confusion Matrix')
```

Out[343]:
```
Text(0.5, 0, 'Actual Value')
```

Out[343]:
```
Text(0, 0.5, 'Predicted Value')
```

Out[343]:
```
([<matplotlib.axis.XTick at 0x299c295cac8>,
  <matplotlib.axis.XTick at 0x299c295c148>,
  <matplotlib.axis.XTick at 0x299c28df848>,
  <matplotlib.axis.XTick at 0x299c2914888>,
  <matplotlib.axis.XTick at 0x299c2916248>,
  <matplotlib.axis.XTick at 0x299c2916948>,
  <matplotlib.axis.XTick at 0x299c29951c8>],
 <a list of 7 Text xticklabel objects>)
```



Auto Neural Network

In [344]:

```
nnclass3 = MLPClassifier(activation='relu', solver='sgd')
nnclass3.fit(steel_data_train_std, y_train)

nnclass3_pred = nnclass3.predict(steel_data_test_std)

print(metrics.classification_report(y_test, nnclass3_pred))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neural_network\multilaye
r_perceptron.py:566: ConvergenceWarning: Stochastic Optimizer: Maximum iter
ations (200) reached and the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
```

Out[344]:

```
MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.
9,
              beta_2=0.999, early_stopping=False, epsilon=1e-08,
              hidden_layer_sizes=(100,), learning_rate='constant',
              learning_rate_init=0.001, max_iter=200, momentum=0.9,
              n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5,
              random_state=None, shuffle=True, solver='sgd', tol=0.0001,
              validation_fraction=0.1, verbose=False, warm_start=False)
```

```
              precision    recall  f1-score   support

       Bumps       0.54      0.60      0.57       115
  Dirtiness       0.91      0.67      0.77        15
   K_Scatch       0.97      0.92      0.94       123
Other_Faults       0.68      0.65      0.67       211
      Pastry       0.41      0.50      0.45        38
      Stains       0.95      0.91      0.93        23
   Z_Scratch       0.86      0.83      0.84        58

    accuracy                           0.72       583
   macro avg       0.76      0.73      0.74       583
weighted avg       0.73      0.72      0.72       583
```

In [345]:

```
nnclass3.hidden_layer_sizes
```

Out[345]:

```
(100,)
```

In [346]:

```
cm = metrics.confusion_matrix(y_test, nnclass2_pred)
print(cm)
```

```
[[ 67   0   1  40   4   0   3]
 [  1   3   0   5   6   0   0]
 [  0   0 114   9   0   0   0]
 [ 44   0   5 140  16   2   4]
 [  6   0   0  10  20   0   2]
 [  1   0   0   3   0  19   0]
 [  2   0   0   5   0   0  51]]
```

Modifying the independent variables

Normalizing the data

In [347]:

```
##Normalizing the data - range transformation
reduc_data = df.loc[:, ~df.columns.isin(['Class','DefType'])]
col_names = reduc_data.columns
reduc_data_values = reduc_data.values
scaler = preprocessing.MinMaxScaler()
reduc_data_scaled = scaler.fit_transform(reduc_data_values)
reduc_norm = pd.DataFrame(reduc_data_scaled,columns = col_names)
reduc_norm
```

Out[347]:

	X_Minimum	X_Maximum	Y_Minimum	Y_Maximum	Pixels_Areas	X_Perimeter	Y_Perim
0	0.024633	0.026916	0.020352	0.020354	0.001736	0.001436	0.002
1	0.378299	0.378584	0.195006	0.195007	0.000694	0.000766	0.001
2	0.486217	0.486249	0.119190	0.119190	0.000452	0.000574	0.000
3	0.500293	0.500878	0.027938	0.027940	0.001140	0.001053	0.002
4	0.756012	0.761849	0.037853	0.037872	0.015768	0.005552	0.014
...	...	...	...	...	...	...	
1936	0.146041	0.159743	0.024580	0.024580	0.001775	0.004978	0.001
1937	0.084457	0.100059	0.025720	0.025720	0.001867	0.004020	0.001
1938	0.085044	0.099473	0.029279	0.029279	0.001900	0.003637	0.001
1939	0.080352	0.097133	0.032030	0.032032	0.002732	0.009094	0.002
1940	0.739589	0.747221	0.006258	0.006259	0.000662	0.002297	0.001

1941 rows × 27 columns

Checking for corelation among independent variables

In [348]:
```
reduc_norm.corr()
```

Out[348]:

	X_Minimum	X_Maximum	Y_Minimum	Y_Maximum	Pixels_Areas	X_
X_Minimum	1.000000	0.988314	0.041821	0.041807	-0.307322	
X_Maximum	0.988314	1.000000	0.052147	0.052135	-0.225399	
Y_Minimum	0.041821	0.052147	1.000000	1.000000	0.017670	
Y_Maximum	0.041807	0.052135	1.000000	1.000000	0.017840	
Pixels_Areas	-0.307322	-0.225399	0.017670	0.017840	1.000000	
X_Perimeter	-0.258937	-0.186326	0.023843	0.024038	0.966644	
Y_Perimeter	-0.118757	-0.090138	0.024150	0.024380	0.827199	
Sum_of_Luminosity	-0.339045	-0.247052	0.007362	0.007499	0.978952	
Minimum_of_Luminosity	0.237637	0.168649	-0.065703	-0.065733	-0.497204	
Maximum_of_Luminosity	-0.075554	-0.062392	-0.067785	-0.067776	0.110063	
Length_of_Conveyer	0.316662	0.299390	-0.049211	-0.049219	-0.155853	
TypeOfSteel_A300	0.144319	0.112009	0.075164	0.075151	-0.235591	
TypeOfSteel_A400	-0.144319	-0.112009	-0.075164	-0.075151	0.235591	
Steel_Plate_Thickness	0.136625	0.106119	-0.207640	-0.207644	-0.183735	
Edges_Index	0.278075	0.242846	0.021314	0.021300	-0.275289	
Empty_Index	-0.198461	-0.152680	-0.043117	-0.043085	0.272808	
Square_Index	0.063658	0.048575	-0.006135	-0.006152	0.017865	
Outside_X_Index	-0.361160	-0.214930	0.054165	0.054185	0.588606	
Edges_X_Index	0.154778	0.149259	0.066085	0.066051	-0.294673	
Edges_Y_Index	0.367907	0.271915	-0.036543	-0.036549	-0.463571	
Outside_Global_Index	0.147282	0.099253	-0.062911	-0.062901	-0.109655	
LogOfAreas	-0.428553	-0.332169	0.044952	0.044994	0.650234	
Log_X_Index	-0.437944	-0.324012	0.070406	0.070432	0.603072	
Log_Y_Index	-0.326851	-0.265990	-0.008442	-0.008382	0.578342	
Orientation_Index	0.178585	0.115019	-0.086497	-0.086480	-0.137604	
Luminosity_Index	-0.031578	-0.038996	-0.090654	-0.090666	-0.043449	
SigmoidOfAreas	-0.355251	-0.286736	0.025257	0.025284	0.422947	

Removing the highly correlated independent variables

In [349]:
```
reduc_filt = reduc_norm.loc[:, ~reduc_norm.columns.isin(['X_Maximum','Y_Maxin
print(reduc_filt.shape)
```

```
(1941, 17)
```

Principal Component Analysis - Normalized Data

In [350]:
```
pca_result = pca(n_components=17).fit(reduc_filt)
#Obtain eigenvalues
pca_result.explained_variance_
```

Out[350]:
```
array([0.30255364, 0.25737568, 0.14203245, 0.07720271, 0.06535347,
       0.0531238 , 0.04855801, 0.04032302, 0.02686413, 0.022293  ,
       0.01633811, 0.01117909, 0.00714101, 0.00253667, 0.00138878,
       0.00056129, 0.00053266])
```

In [351]:

```
#plotting PCA
plt.figure(figsize=(7,5))
plt.plot([1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16, 17], pca_result.explained_v
plt.ylabel('Proportion of Variance Explained')
plt.xlabel('Principal Component')
#plt.xlim(0.75,4.25)
#plt.ylim(0,1.05)
plt.xticks([1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16, 17])
```

Out[351]:

```
<Figure size 504x360 with 0 Axes>
```

Out[351]:

```
[<matplotlib.lines.Line2D at 0x299c29b4bc8>]
```

Out[351]:

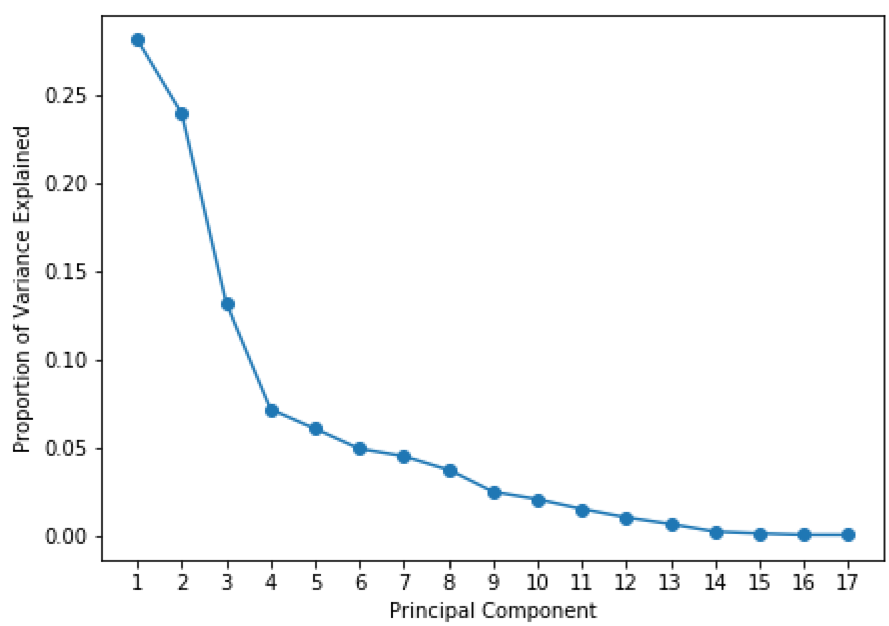
```
Text(0, 0.5, 'Proportion of Variance Explained')
```

Out[351]:

```
Text(0.5, 0, 'Principal Component')
```

Out[351]:

```
([<matplotlib.axis.XTick at 0x299c29ba6c8>,
  <matplotlib.axis.XTick at 0x299bd4fa388>,
  <matplotlib.axis.XTick at 0x299c294a888>,
  <matplotlib.axis.XTick at 0x299c29b51c8>,
  <matplotlib.axis.XTick at 0x299c29b5988>,
  <matplotlib.axis.XTick at 0x299c2967108>,
  <matplotlib.axis.XTick at 0x299c29af988>,
  <matplotlib.axis.XTick at 0x299c29afbc8>,
  <matplotlib.axis.XTick at 0x299c29b3bc8>,
  <matplotlib.axis.XTick at 0x299c29b38c8>,
  <matplotlib.axis.XTick at 0x299c29b2bc8>,
  <matplotlib.axis.XTick at 0x299c29b82c8>,
  <matplotlib.axis.XTick at 0x299c29b8b48>,
  <matplotlib.axis.XTick at 0x299c29b8c48>,
  <matplotlib.axis.XTick at 0x299c29a9bc8>,
  <matplotlib.axis.XTick at 0x299c29c0608>,
  <matplotlib.axis.XTick at 0x299c29c0e88>],
 <a list of 17 Text xticklabel objects>)
```



Factor Analysis

In [352]:
```
fa = FactorAnalyzer(9,rotation='varimax')
fa.fit(reduc_filt)
fa.loadings_
```

Out[352]:
```
FactorAnalyzer(bounds=(0.005, 1), impute='median', is_corr_matrix=False,
               method='minres', n_factors=9, rotation='varimax',
               rotation_kwargs={}, use_smc=True)
```

Out[352]:
```
array([[ 0.33844407, -0.04467156,  0.05897517,  0.00892601, -0.04800935,
         0.64851618,  0.02186099, -0.04142992,  0.05163826],
       [-0.01328759, -0.06920228, -0.03499891,  0.04844939, -0.01424139,
         0.04533559, -0.03528067, -0.41879793,  0.03125152],
       [-0.72074514,  0.05670127,  0.0417465 , -0.089478  ,  0.13270463,
        -0.10070663,  0.1011614 , -0.07000087,  0.0541188 ],
       [ 0.74199926,  0.54179381, -0.04402201, -0.01837413,  0.14797361,
         0.03733792, -0.01443793,  0.06520432,  0.06253286],
       [-0.0680706 ,  0.89982635, -0.06134579, -0.06172601, -0.03008206,
        -0.0147013 ,  0.0262933 ,  0.00520856, -0.00274686],
       [ 0.0422524 , -0.07748696,  0.03156894,  0.33985495, -0.23333652,
         0.45154258,  0.03897444,  0.20986452, -0.0821435 ],
       [ 0.20058351, -0.1649933 , -0.02692938,  0.95248404, -0.00339229,
         0.08776957,  0.10045671, -0.04067847,  0.03059028],
       [ 0.15662106, -0.11157481,  0.12417299,  0.10497948,  0.04047146,
         0.15178128, -0.14306714,  0.5444327 ,  0.08100534],
       [ 0.35419702,  0.17752288, -0.05143901,  0.03698364, -0.08560933,
         0.24708459,  0.11268649, -0.01915752,  0.07701451],
       [-0.23587972,  0.03629773, -0.02064437, -0.02012922,  0.73473651,
        -0.11963355, -0.03487342,  0.073519  , -0.01082887],
       [ 0.06421641,  0.05923367, -0.07702312,  0.07855792, -0.03956167,
         0.04517189,  0.77518524, -0.03880839,  0.00952248],
       [-0.75356941,  0.04681758, -0.29746262, -0.08637265,  0.19271434,
        -0.13349901, -0.0967648 , -0.11817857,  0.08639293],
       [ 0.30872356,  0.06221269, -0.77756023,  0.07095359, -0.42040798,
         0.090543  ,  0.15960372, -0.05478872,  0.27370287],
       [ 0.58744241, -0.11621573,  0.47466621,  0.08991385, -0.39992519,
         0.1555088 ,  0.07998125,  0.102352  ,  0.38042246],
       [ 0.12740829, -0.07893841,  0.69026662,  0.00282869, -0.15139386,
         0.07819046, -0.04281443,  0.1463228 ,  0.10609889],
       [-0.87309107, -0.05623831,  0.09138196, -0.13068968,  0.16868582,
        -0.17634411, -0.13516937, -0.07281583, -0.14336892],
       [ 0.17279672,  0.96393867, -0.07136082, -0.136412  ,  0.07667582,
        -0.06051132,  0.06990843,  0.01728517, -0.01983381]])
```

Converting the factor analysis results into dataframe

In [353]:

```
fa_load_df = pd. DataFrame([[ 0.33844407, -0.04467156,  0.05897517,  0.008926
          0.64851618,  0.02186099, -0.04142992,  0.05163826],
        [-0.01328759, -0.06920228, -0.03499891,  0.04844939, -0.01424139,
          0.04533559, -0.03528067, -0.41879793,  0.03125152],
        [-0.72074514,  0.05670127,  0.0417465 , -0.089478  ,  0.13270463,
         -0.10070663,  0.1011614 , -0.07000087,  0.0541188 ],
        [ 0.74199926,  0.54179381, -0.04402201, -0.01837413,  0.14797361,
          0.03733792, -0.01443793,  0.06520432,  0.06253286],
        [-0.0680706 ,  0.89982635, -0.06134579, -0.06172601, -0.03008206,
         -0.0147013 ,  0.0262933 ,  0.00520856, -0.00274686],
        [ 0.0422524 , -0.07748696,  0.03156894,  0.33985495, -0.23333652,
          0.45154258,  0.03897444,  0.20986452, -0.0821435 ],
        [ 0.20058351, -0.1649933 , -0.02692938,  0.95248404, -0.00339229,
          0.08776957,  0.10045671, -0.04067847,  0.03059028],
        [ 0.15662106, -0.11157481,  0.12417299,  0.10497948,  0.04047146,
          0.15178128, -0.14306714,  0.5444327 ,  0.08100534],
        [ 0.35419702,  0.17752288, -0.05143901,  0.03698364, -0.08560933,
          0.24708459,  0.11268649, -0.01915752,  0.07701451],
        [-0.23587972,  0.03629773, -0.02064437, -0.02012922,  0.73473651,
         -0.11963355, -0.03487342,  0.073519  , -0.01082887],
        [ 0.06421641,  0.05923367, -0.07702312,  0.07855792, -0.03956167,
          0.04517189,  0.77518524, -0.03880839,  0.00952248],
        [-0.75356941,  0.04681758, -0.29746262, -0.08637265,  0.19271434,
         -0.13349901, -0.0967648 , -0.11817857,  0.08639293],
        [ 0.30872356,  0.06221269, -0.77756023,  0.07095359, -0.42040798,
          0.090543  ,  0.15960372, -0.05478872,  0.27370287],
        [ 0.58744241, -0.11621573,  0.47466621,  0.08991385, -0.39992519,
          0.1555088 ,  0.07998125,  0.102352  ,  0.38042246],
        [ 0.12740829, -0.07893841,  0.69026662,  0.00282869, -0.15139386,
          0.07819046, -0.04281443,  0.1463228 ,  0.10609889],
        [-0.87309107, -0.05623831,  0.09138196, -0.13068968,  0.16868582,
         -0.17634411, -0.13516937, -0.07281583, -0.14336892],
        [ 0.17279672,  0.96393867, -0.07136082, -0.136412  ,  0.07667582,
         -0.06051132,  0.06990843,  0.01728517, -0.01983381]],columns = ["f1",
fa_load_df
```

Out[353]:

	f1	f2	f3	f4	f5	f6
X_Minimum	0.338444	-0.044672	0.058975	0.008926	-0.048009	0.648516
Y_Minimum	-0.013288	-0.069202	-0.034999	0.048449	-0.014241	0.045336
Pixels_Areas	-0.720745	0.056701	0.041746	-0.089478	0.132705	-0.100707
Minimum_of_Luminosity	0.741999	0.541794	-0.044022	-0.018374	0.147974	0.037338
Maximum_of_Luminosity	-0.068071	0.899826	-0.061346	-0.061726	-0.030082	-0.014701
Length_of_Conveyer	0.042252	-0.077487	0.031569	0.339855	-0.233337	0.451543
TypeOfSteel_A300	0.200584	-0.164993	-0.026929	0.952484	-0.003392	0.087770
Steel_Plate_Thickness	0.156621	-0.111575	0.124173	0.104979	0.040471	0.151781
Edges_Index	0.354197	0.177523	-0.051439	0.036984	-0.085609	0.247085
Empty_Index	-0.235880	0.036298	-0.020644	-0.020129	0.734737	-0.119634

	f1	f2	f3	f4	f5	f6
Square_Index	0.064216	0.059234	-0.077023	0.078558	-0.039562	0.045172
Outside_X_Index	-0.753569	0.046818	-0.297463	-0.086373	0.192714	-0.133499
Edges_X_Index	0.308724	0.062213	-0.777560	0.070954	-0.420408	0.090543
Edges_Y_Index	0.587442	-0.116216	0.474666	0.089914	-0.399925	0.155509
Outside_Global_Index	0.127408	-0.078938	0.690267	0.002829	-0.151394	0.078190
LogOfAreas	-0.873091	-0.056238	0.091382	-0.130690	0.168686	-0.176344
Luminosity_Index	0.172797	0.963939	-0.071361	-0.136412	0.076676	-0.060511

In [354]:

```
#selecting the highest variance shared variable from each factor
'LogOfAreas','Luminosity_Index','Edges_X_Index','TypeOfSteel_A300','Empty_Inc
```

Out[354]:

```
('LogOfAreas',
 'Luminosity_Index',
 'Edges_X_Index',
 'TypeOfSteel_A300',
 'Empty_Index',
 'X_Minimum',
 'Square_Index',
 'Steel_Plate_Thickness',
 'Edges_Y_Index')
```

Variable Clustering Algorithm to Cluster the Independent variables

In [355]:

```
demo1_vc = VarClusHi(reduc_filt,maxeigval2=1,maxclus=9)
demo1_vc.varclus()
demo1_vc.info
```

Out[355]:

```
<varclushi.varclushi.VarClusHi at 0x299c29d8108>
```

Out[355]:

	Cluster	N_Vars	Eigval1	Eigval2	VarProp
0	0	7	3.563414	0.888506	0.509059
1	1	4	2.341821	0.987472	0.585455
2	2	4	1.611411	0.944601	0.402853
3	3	2	1.378542	0.621458	0.689271

Variable clustering algorithm suggested 4 clusters

In [356]:
```
demo1_vc.rsquare
```

Out[356]:

	Cluster	Variable	RS_Own	RS_NC	RS_Ratio
0	0	X_Minimum	0.322580	0.077076	0.733993
1	0	Pixels_Areas	0.552038	0.055576	0.474323
2	0	Edges_Index	0.257274	0.067423	0.796423
3	0	Empty_Index	0.288507	0.037736	0.739395
4	0	Outside_X_Index	0.709134	0.077478	0.315294
5	0	Edges_Y_Index	0.664701	0.082306	0.365371
6	0	LogOfAreas	0.769180	0.099157	0.256227
7	1	Y_Minimum	0.021915	0.014246	0.992220
8	1	Minimum_of_Luminosity	0.598967	0.306919	0.578623
9	1	Maximum_of_Luminosity	0.781264	0.035840	0.226867
10	1	Luminosity_Index	0.939675	0.058785	0.064092
11	2	Steel_Plate_Thickness	0.219306	0.049426	0.821287
12	2	Edges_X_Index	0.590130	0.119298	0.465389
13	2	Square_Index	0.236481	0.020519	0.779514
14	2	Outside_Global_Index	0.565493	0.089500	0.477218
15	3	Length_of_Conveyer	0.689271	0.084008	0.339226
16	3	TypeOfSteel_A300	0.689271	0.087599	0.340561

Predictive Modelling - Variables suggested by factor analysis

In [357]:
```
#variables are
#'LogOfAreas','Luminosity_Index','Edges_X_Index','TypeOfSteel_A300','Empty_Ir
```

In [358]:
```
reduc_factor = reduc_filt.loc[:, reduc_filt.columns.isin(['LogOfAreas','Lumir
```

Splitting the data into training and testing

In [359]:

```
Y_cat = df.loc[:, 'DefType']
print(len(Y_cat.unique()))
Y_cat.head()
```

```
7
```

Out[359]:

```
0    Pastry
1    Pastry
2    Pastry
3    Pastry
4    Pastry
Name: DefType, dtype: object
```

In [360]:

```
X_train, X_test, y_train, y_test = train_test_split(reduc_factor, Y_cat, test
```

In [361]:

```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(1358, 9)
(583, 9)
(1358,)
(583,)
```

Decision Trees

In [362]:

```
col_names = list(reduc_factor.columns.values)
classnames = list(df.DefType.unique())
col_names
```

Out[362]:

```
['X_Minimum',
 'TypeOfSteel_A300',
 'Steel_Plate_Thickness',
 'Empty_Index',
 'Square_Index',
 'Edges_X_Index',
 'Edges_Y_Index',
 'LogOfAreas',
 'Luminosity_Index']
```

In [363]:

```
##Performing Descision trees using all categories
tre2 = tree.DecisionTreeClassifier().fit(X_train,y_train)

predicted = tre2.predict(X_test)

print(metrics.classification_report(y_test, predicted))
```

```
              precision    recall  f1-score   support

       Bumps       0.49      0.56      0.53       110
   Dirtiness       0.60      0.60      0.60        15
    K_Scatch       0.96      0.88      0.92       120
Other_Faults       0.64      0.64      0.64       215
      Pastry       0.41      0.41      0.41        37
      Stains       0.91      0.91      0.91        23
   Z_Scratch       0.78      0.75      0.76        63

    accuracy                           0.68       583
   macro avg       0.69      0.68      0.68       583
weighted avg       0.69      0.68      0.68       583
```

In [364]:

```
##Performing Descision trees using all categories
cm = metrics.confusion_matrix(y_test, predicted)
print(cm)
```

```
[[ 62   0   0  39   7   0   2]
 [  0   9   0   5   1   0   0]
 [  2   0 105  13   0   0   0]
 [ 46   3   3 137  13   2  11]
 [ 12   2   0   8  15   0   0]
 [  1   0   0   1   0  21   0]
 [  3   1   1  10   1   0  47]]
```

In [365]:

```
#cm chart
plt.matshow(cm)
plt.title('Confusion Matrix')
plt.xlabel('Actual Value')
plt.ylabel('Predicted Value')
plt.xticks([0,1,2,3,4,5,6], ['I','II','III','IV','V','VI','VII'])
```

Out[365]:

```
<matplotlib.image.AxesImage at 0x299c0a45f88>
```

Out[365]:

```
Text(0.5, 1.05, 'Confusion Matrix')
```

Out[365]:

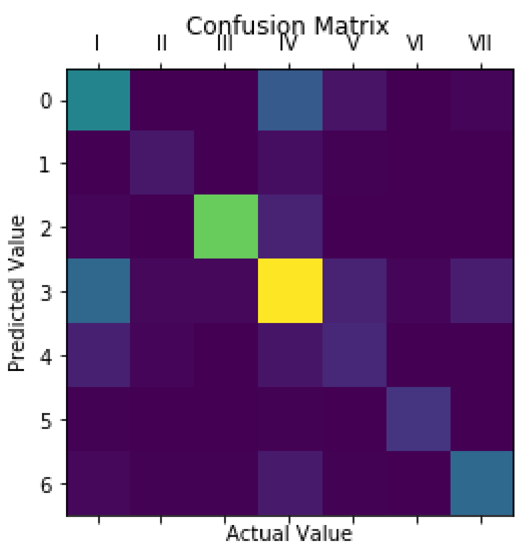
```
Text(0.5, 0, 'Actual Value')
```

Out[365]:

```
Text(0, 0.5, 'Predicted Value')
```

Out[365]:

```
([<matplotlib.axis.XTick at 0x299c29d3a08>,
  <matplotlib.axis.XTick at 0x299c0a40d88>,
  <matplotlib.axis.XTick at 0x299c0a45908>,
  <matplotlib.axis.XTick at 0x299c0a4a888>,
  <matplotlib.axis.XTick at 0x299c0a4acc8>,
  <matplotlib.axis.XTick at 0x299c0a4b648>,
  <matplotlib.axis.XTick at 0x299c0a4bf08>],
 <a list of 7 Text xticklabel objects>)
```

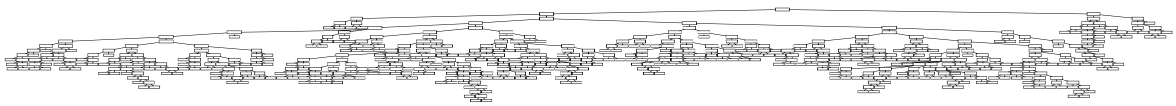


Important Features in the decision tree model

In [366]:
```
eli5.show_weights(tre2,feature_names = list(X_test.columns),top=None)
```

Out[366]:

Weight	Feature
0.2995	LogOfAreas
0.1495	X_Minimum
0.1192	Steel_Plate_Thickness
0.0910	Edges_X_Index
0.0883	Square_Index
0.0841	Luminosity_Index
0.0796	Empty_Index
0.0541	Edges_Y_Index
0.0348	TypeOfSteel_A300



In [367]:
```
print("Actual defect value is:",y_test.iloc[101])
test_row = pd.DataFrame(X_test.iloc[101,:]).T
test_row
```

```
Actual defect value is: Other_Faults
```

Out[367]:

	X_Minimum	TypeOfSteel_A300	Steel_Plate_Thickness	Empty_Index	Square_Index	Edge
1790	0.124927	1.0	0.230769	0.454074	0.495815	

Contribution of feature in predicting the category

In [368]:
```
#eli5.show_prediction(tre2, test_row.values[0],feature_names=list(X_test.colu
lid = [101]
for i in lid:
    print("Actual test value:",y_test.iloc[i])
    print("------------")
    print("Pedidcted value is ")

eli5.show_prediction(tre2, X_test.iloc[i], feature_names = list(X_train.colum
```

```
Actual test value: Other_Faults
------------
Pedidcted value is
```

Out[368]:

y=Bumps (probability **0.000**) top features		**y=Dirtiness** (probability **0.000**) top features		**y=K_Scatch** (probabi features	
Contribution?	**Feature**	**Contribution?**	**Feature**	**Contribution?**	**Feat**
+0.319	Steel_Plate_Thickness	+0.029	<BIAS>	+0.200	<BIA
+0.215	<BIAS>	+0.008	LogOfAreas	-0.002	X_M
+0.116	TypeOfSteel_A300	-0.006	Steel_Plate_Thickness	-0.046	Type
-0.195	X_Minimum	-0.006	X_Minimum	-0.152	Log(
-0.455	LogOfAreas	-0.026	TypeOfSteel_A300		

Building Random Forest Model

In [369]:

```
##Performing random forest using all categories
from sklearn.ensemble import RandomForestClassifier
rand1 = RandomForestClassifier().fit(X_train,y_train)

rand1_pred = rand1.predict(X_test)

print(metrics.classification_report(y_test, rand1_pred))
```

```
              precision    recall  f1-score   support

       Bumps       0.54      0.62      0.57       110
   Dirtiness       0.62      0.53      0.57        15
    K_Scatch       0.93      0.96      0.95       120
Other_Faults       0.69      0.71      0.70       215
      Pastry       0.52      0.38      0.44        37
      Stains       1.00      0.91      0.95        23
   Z_Scratch       0.88      0.71      0.79        63

    accuracy                           0.73       583
   macro avg       0.74      0.69      0.71       583
weighted avg       0.73      0.73      0.73       583


C:\ProgramData\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:245:
FutureWarning: The default value of n_estimators will change from 10 in ver
sion 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

In [370]:

```
##Performing random forest using all categories
cm = metrics.confusion_matrix(y_test, rand1_pred)
print(cm)
```

```
[[ 68   1   1  35   4   0   1]
 [  0   8   0   5   2   0   0]
 [  0   0 115   5   0   0   0]
 [ 43   3   6 153   5   0   5]
 [ 10   0   0  13  14   0   0]
 [  1   0   0   1   0  21   0]
 [  5   1   1   9   2   0  45]]
```

Feature Importance

In [371]:
```
eli5.show_weights(rand1,feature_names=list(X_test.columns),top=None)
```

Out[371]:

Weight	Feature
0.1944 ± 0.1533	LogOfAreas
0.1611 ± 0.1101	X_Minimum
0.1273 ± 0.1000	Steel_Plate_Thickness
0.1103 ± 0.0386	Luminosity_Index
0.1071 ± 0.0313	Square_Index
0.0933 ± 0.0390	Empty_Index
0.0855 ± 0.0840	Edges_Y_Index
0.0819 ± 0.0243	Edges_X_Index
0.0392 ± 0.0203	TypeOfSteel_A300

Neural Network

In [372]:
```
# Standardize the scaling of the variables by
# computing the mean and std to be used for later scaling.
scaler = preprocessing.StandardScaler()
scaler.fit(X_train)

# Perform the standardization process
steel_data_train_std = scaler.transform(X_train)
steel_data_test_std = scaler.transform(X_test)
```

Out[372]:
```
StandardScaler(copy=True, with_mean=True, with_std=True)
```

In [373]:

```
nnclass2 = MLPClassifier(activation='relu', solver='sgd',
                         hidden_layer_sizes=(50,50,50))
nnclass2.fit(steel_data_train_std, y_train)

nnclass2_pred = nnclass2.predict(steel_data_test_std)

print(metrics.classification_report(y_test, nnclass2_pred))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neural_network\multilaye
r_perceptron.py:566: ConvergenceWarning: Stochastic Optimizer: Maximum iter
ations (200) reached and the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
```

Out[373]:

```
MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.
9,
              beta_2=0.999, early_stopping=False, epsilon=1e-08,
              hidden_layer_sizes=(50, 50, 50), learning_rate='constant',
              learning_rate_init=0.001, max_iter=200, momentum=0.9,
              n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5,
              random_state=None, shuffle=True, solver='sgd', tol=0.0001,
              validation_fraction=0.1, verbose=False, warm_start=False)
```

```
              precision    recall  f1-score   support

       Bumps       0.53      0.46      0.50       110
   Dirtiness       0.00      0.00      0.00        15
    K_Scatch       0.96      0.93      0.94       120
Other_Faults       0.63      0.72      0.67       215
      Pastry       0.42      0.38      0.40        37
      Stains       0.94      0.65      0.77        23
   Z_Scratch       0.64      0.79      0.71        63

    accuracy                           0.68       583
   macro avg       0.59      0.56      0.57       583
weighted avg       0.66      0.68      0.67       583
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\classification.p
y:1437: UndefinedMetricWarning: Precision and F-score are ill-defined and b
eing set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

In [374]:

```
cm = metrics.confusion_matrix(y_test, nnclass2_pred)
print(cm)
```

```
[[ 51   0   0  43   3   0  13]
 [  0   0   0  10   5   0   0]
 [  0   0 111   9   0   0   0]
 [ 33   0   4 154  11   1  12]
 [  4   0   0  16  14   0   3]
 [  1   0   0   7   0  15   0]
 [  7   0   1   5   0   0  50]]
```

In [375]:
```
plt.matshow(cm)
plt.title('Confusion Matrix')
plt.xlabel('Actual Value')
plt.ylabel('Predicted Value')
plt.xticks([0,1,2,3,4,5,6], ['I','II','III','IV','V','VI','VII'])
```

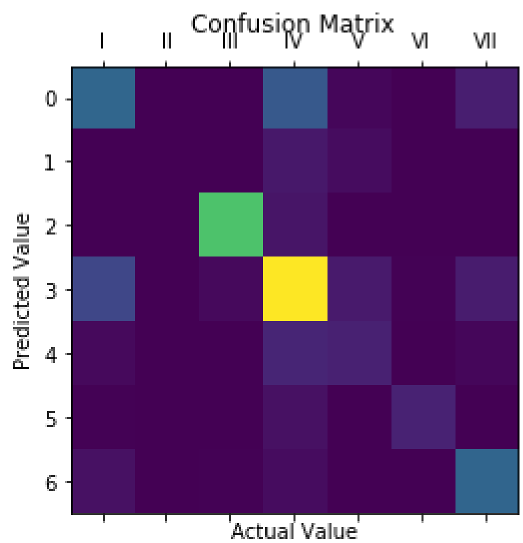
Out[375]:
```
<matplotlib.image.AxesImage at 0x299c0a66908>
```

Out[375]:
```
Text(0.5, 1.05, 'Confusion Matrix')
```

Out[375]:
```
Text(0.5, 0, 'Actual Value')
```

Out[375]:
```
Text(0, 0.5, 'Predicted Value')
```

Out[375]:
```
([<matplotlib.axis.XTick at 0x299c0a4ca08>,
  <matplotlib.axis.XTick at 0x299c0a37048>,
  <matplotlib.axis.XTick at 0x299c0a66248>,
  <matplotlib.axis.XTick at 0x299c0a5ae88>,
  <matplotlib.axis.XTick at 0x299c0a5a2c8>,
  <matplotlib.axis.XTick at 0x299c0a5d388>,
  <matplotlib.axis.XTick at 0x299c0a5dec8>],
 <a list of 7 Text xticklabel objects>)
```



Auto Neural Network

In [376]:
```
nnclass3 = MLPClassifier(activation='relu', solver='sgd')
nnclass3.fit(steel_data_train_std, y_train)

nnclass3_pred = nnclass3.predict(steel_data_test_std)

print(metrics.classification_report(y_test, nnclass3_pred))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neural_network\multilaye
r_perceptron.py:566: ConvergenceWarning: Stochastic Optimizer: Maximum iter
ations (200) reached and the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
```

Out[376]:
```
MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.
9,
              beta_2=0.999, early_stopping=False, epsilon=1e-08,
              hidden_layer_sizes=(100,), learning_rate='constant',
              learning_rate_init=0.001, max_iter=200, momentum=0.9,
              n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5,
              random_state=None, shuffle=True, solver='sgd', tol=0.0001,
              validation_fraction=0.1, verbose=False, warm_start=False)
```

```
              precision    recall  f1-score   support

       Bumps       0.55      0.49      0.52       110
   Dirtiness       0.00      0.00      0.00        15
    K_Scatch       0.93      0.95      0.94       120
Other_Faults       0.64      0.72      0.67       215
      Pastry       0.45      0.49      0.47        37
      Stains       1.00      0.39      0.56        23
   Z_Scratch       0.67      0.75      0.71        63

    accuracy                           0.68       583
   macro avg       0.60      0.54      0.55       583
weighted avg       0.67      0.68      0.67       583
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\classification.p
y:1437: UndefinedMetricWarning: Precision and F-score are ill-defined and b
eing set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

In [377]:
```
nnclass3.hidden_layer_sizes
```

Out[377]:
```
(100,)
```

In [378]:
```
cm = metrics.confusion_matrix(y_test, nnclass3_pred)
print(cm)
```

```
[[ 54   0   0  42   2   0  12]
 [  0   0   0   8   7   0   0]
 [  0   0 114   6   0   0   0]
 [ 31   0   8 154  13   0   9]
 [  4   0   0  13  18   0   2]
 [  4   0   0  10   0   9   0]
 [  6   0   1   9   0   0  47]]
```

In [ ]:
```

```