rocks-classification

October 27, 2024

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[4]:
```python
rock_data = pd.read_excel("aggregateRockData-1.xlsx", usecols=[1], nrows=480,␣
 ↪names=["rock category"])
attribute_data = pd.read_csv("norm540.txt", sep='\t', usecols=list(range(3,␣
 ↪22)), nrows=480)
token_data=pd.read_csv("norm540.txt", sep='\t', usecols=[2], nrows=480,␣
 ↪names=["Token Number"])
```

Displaying the statistical values for each of the attributes, along with visualizations (e.g., histogram) of the distributions for each attribute.

[5]:
```python
# Assign meaningful column names
attribute_names = [
    "Porphyritic texture",
    "Presence of holes",
    "Salient green hue",
    "Pegmatitic texture",
    "Conchoidal fracture",
    "Angular fragments",
    "Rounded fragments",
    "Straight stripes",
    "Curved stripes",
    "Physical layers",
    "Veins",
    "Oily/shimmery texture",
    "Splotchy texture",
    "Single translucent crystal",
    "Multiple cubic crystals",
    "Sandy texture",
    "Fragments (disjunctive)",
    "Stripes (disjunctive)",
    "Crystals (disjunctive)"
]
```

```python
attribute_data.columns = attribute_names
```

Statistical descriptions

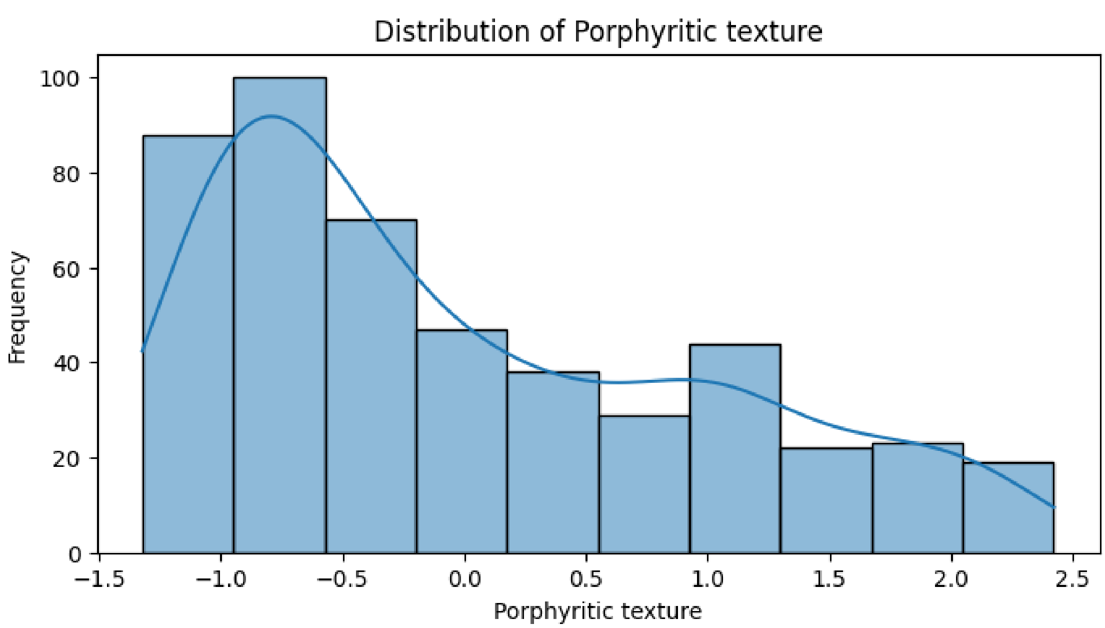
[6]:
```python
# Display summary statistics
statistics = attribute_data.describe()
print(statistics)
```

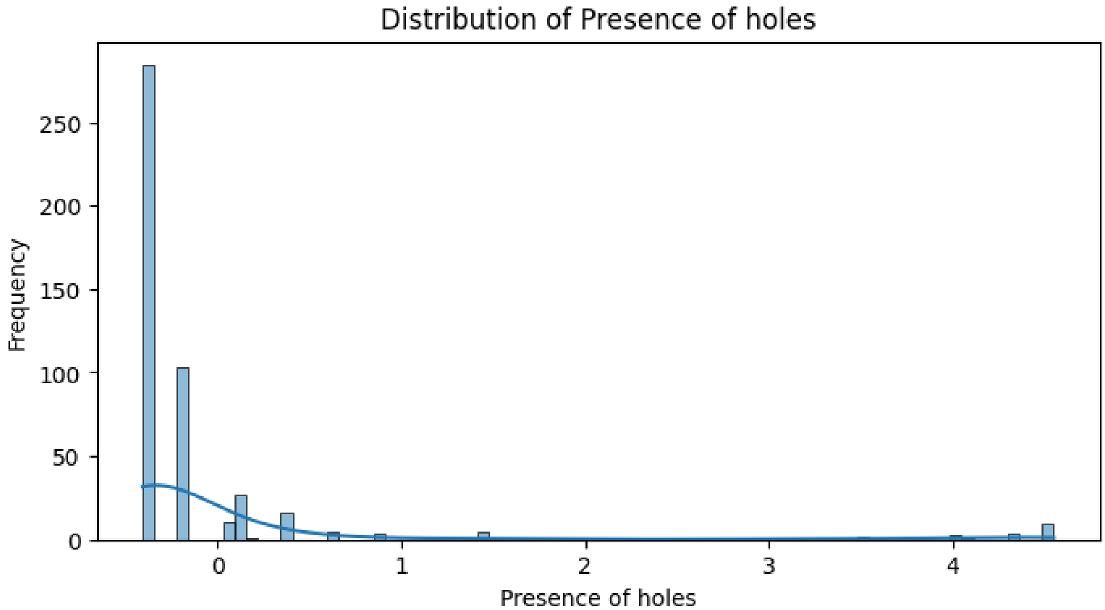
```
       Porphyritic texture  Presence of holes  Salient green hue  \
count           480.000000         480.000000         480.000000
mean              0.000452          -0.019915          -0.002570
std               1.001392           0.990022           0.993719
min              -1.321491          -0.407623          -1.187950
25%              -0.823647          -0.407623          -0.761505
50%              -0.300910          -0.407623          -0.375197
75%               0.766966          -0.159688           0.517828
max               2.422299           4.551072           2.750390

       Pegmatitic texture  Conchoidal fracture  Angular fragments  \
count          480.000000           480.000000         480.000000
mean            -0.000836            -0.012302          -0.006879
std              0.979725             0.997488           0.985432
min             -1.322715            -1.248012          -0.436004
25%             -0.804631            -0.699145          -0.436004
50%             -0.165660            -0.284303          -0.436004
75%              0.576929             0.357107          -0.182021
max              4.175892             3.813059           4.643652

       Rounded fragments  Straight stripes  Curved stripes  Physical layers  \
count         480.000000        480.000000      480.000000       480.000000
mean            0.011081          0.002554       -0.001276         0.000504
std             1.028314          1.020964        0.985604         0.996473
min            -0.405184         -0.352386       -0.260224        -0.759128
25%            -0.405184         -0.352386       -0.260224        -0.759128
50%            -0.405184         -0.352386       -0.260224        -0.299173
75%            -0.145018         -0.352386       -0.260224         0.218277
max             4.798130          4.888957        5.862693         3.610446

            Veins  Oily/shimmery texture  Splotchy texture  \
count  480.000000             480.000000        480.000000
mean     0.010035               0.000827         -0.000623
std      1.023300               0.995705          1.006313
min     -0.512160              -0.540653         -0.846887
25%     -0.512160              -0.540653         -0.846887
50%     -0.512160              -0.540653         -0.249084
75%     -0.013842              -0.165887          0.348718
max      8.457556               3.207009          4.832237
```

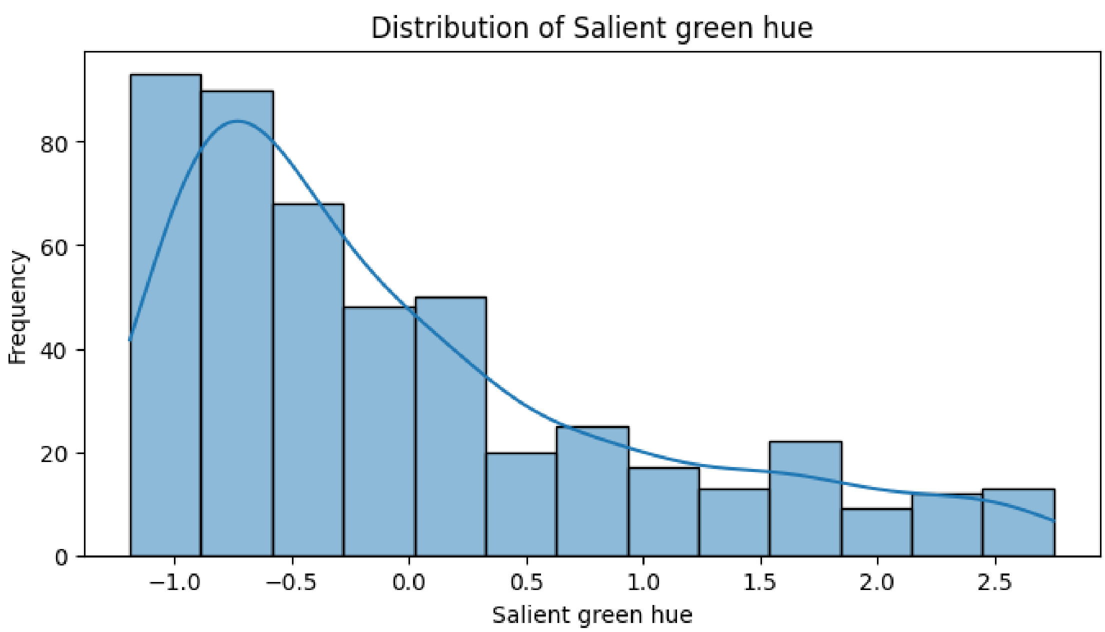
```
       Single translucent crystal  Multiple cubic crystals  Sandy texture  \
count                  480.000000               480.000000     480.000000
mean                     0.004763                -0.018912      -0.003855
std                      0.996726                 0.920901       0.986349
min                     -0.227922                -0.225045      -0.685937
25%                     -0.227922                -0.225045      -0.685937
50%                     -0.227922                -0.225045      -0.401124
75%                     -0.227922                -0.225045       0.168500
max                      7.120010                 7.986072       5.010309

       Fragments (disjunctive)  Stripes (disjunctive)  Crystals (disjunctive)
count               480.000000             480.000000              480.000000
mean                  0.003679              -0.001351               -0.010683
std                   1.004865               1.006172                0.966634
min                  -0.541391              -0.409247               -0.310419
25%                  -0.541391              -0.409247               -0.310419
50%                  -0.541391              -0.409247               -0.310419
75%                   0.010423              -0.207298               -0.310419
max                   3.137369               3.629722                5.216791
```

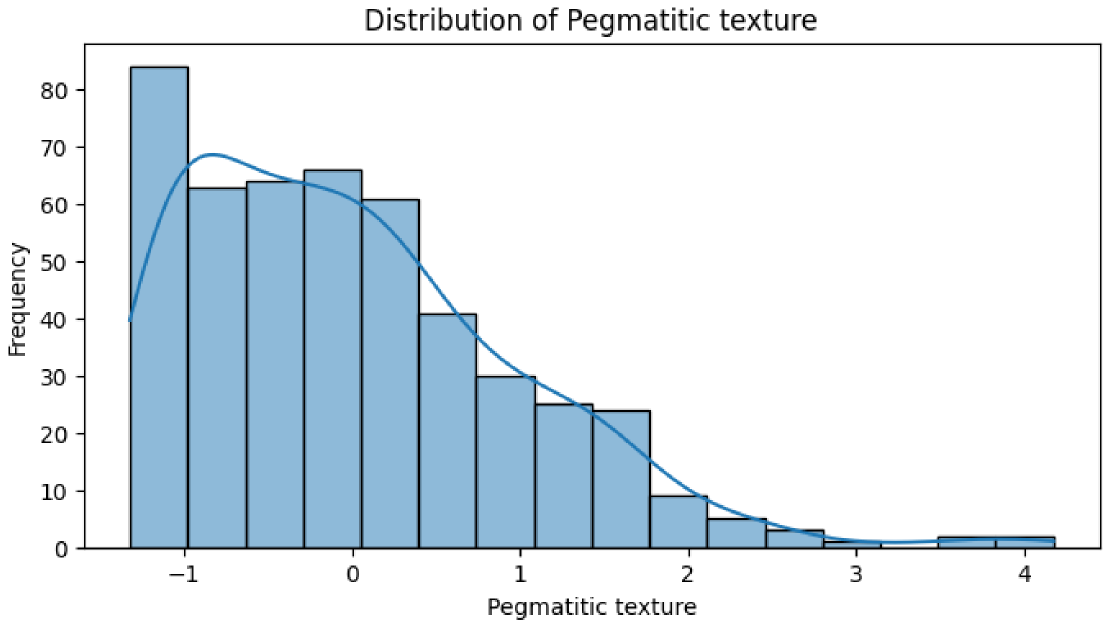
Visualizations

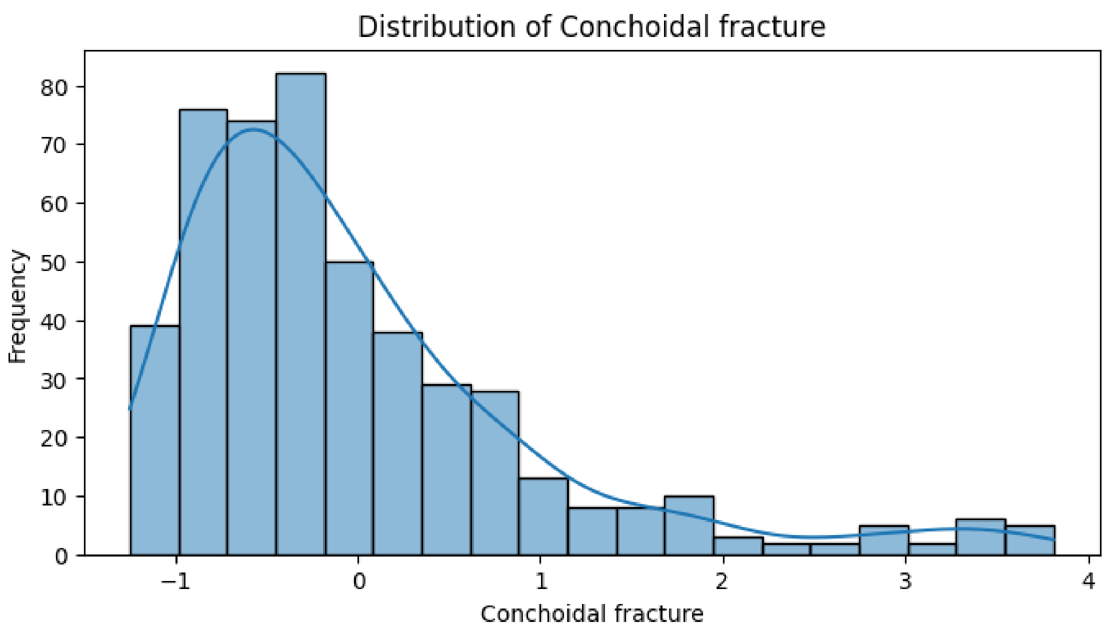
[7]:
```python
# Plot histograms for each attribute
for column in attribute_data.columns:
    plt.figure(figsize=(8, 4))
    sns.histplot(attribute_data[column], kde=True)
    plt.title(f'Distribution of {column}')
    plt.xlabel(column)
    plt.ylabel("Frequency")
    plt.show()
```

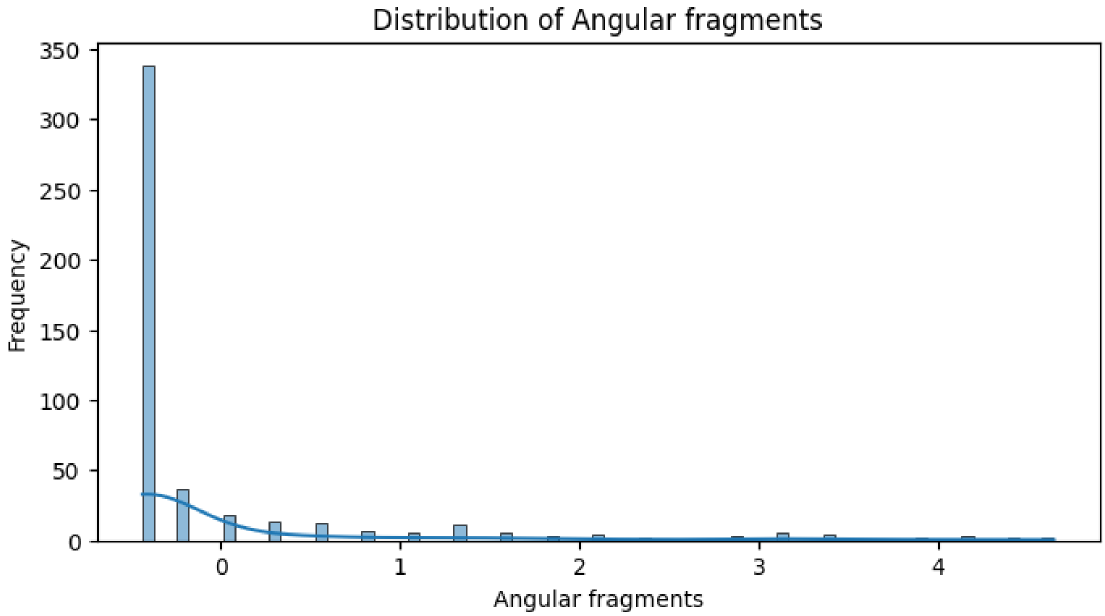


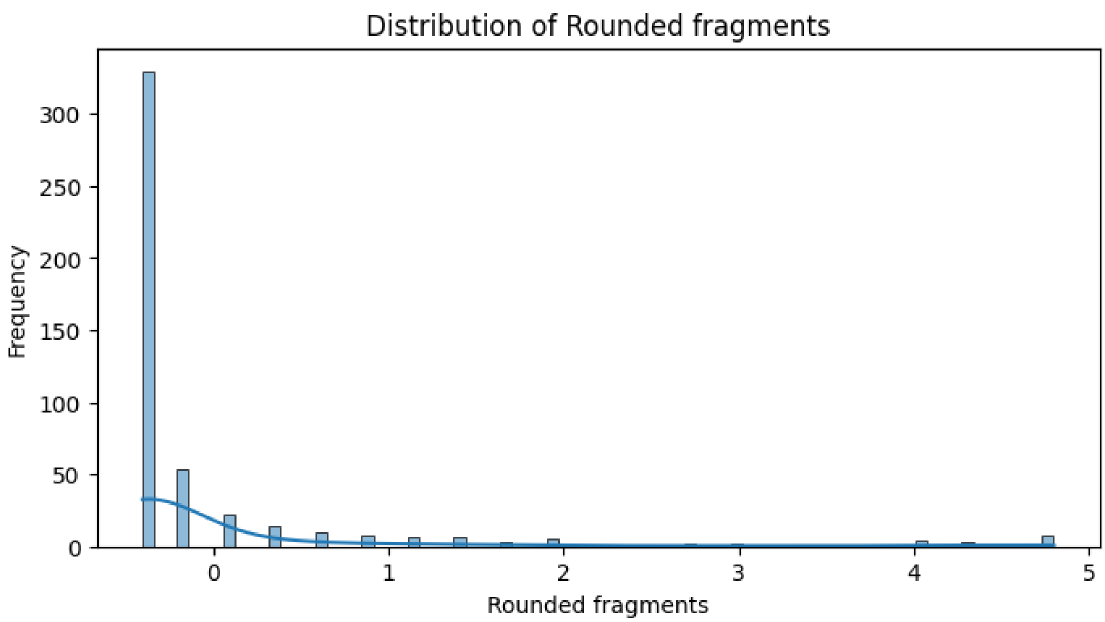

Distribution of Presence of holes
Frequency
0
50
100
150
200
250
0
1
2
3
4
Presence of holes

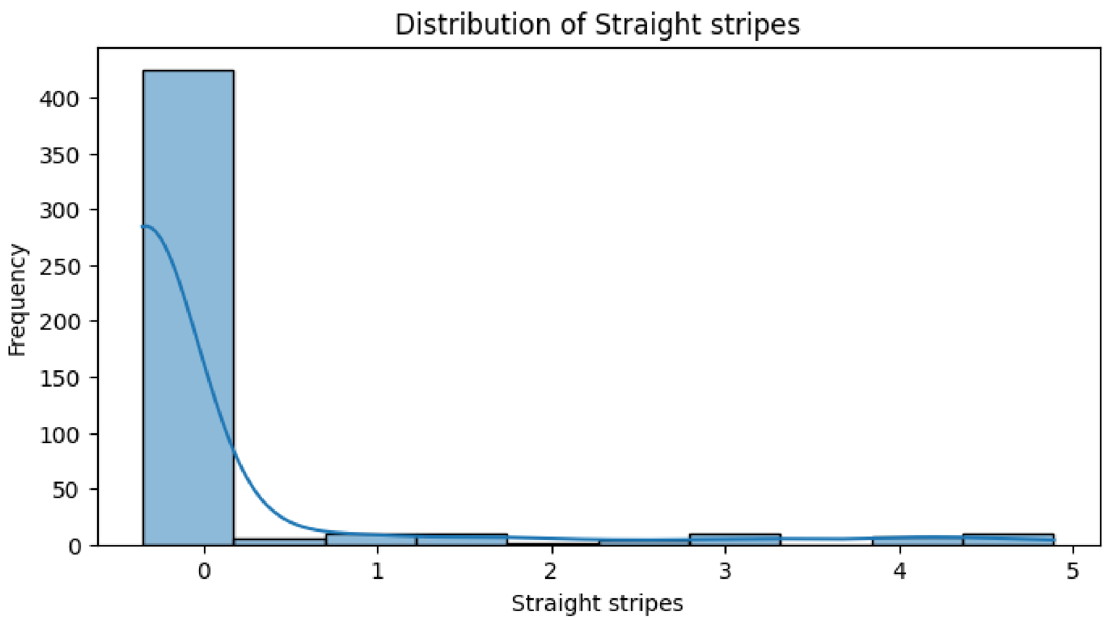

Distribution of Salient green hue
Frequency
0
20
40
60
80
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
Salient green hue

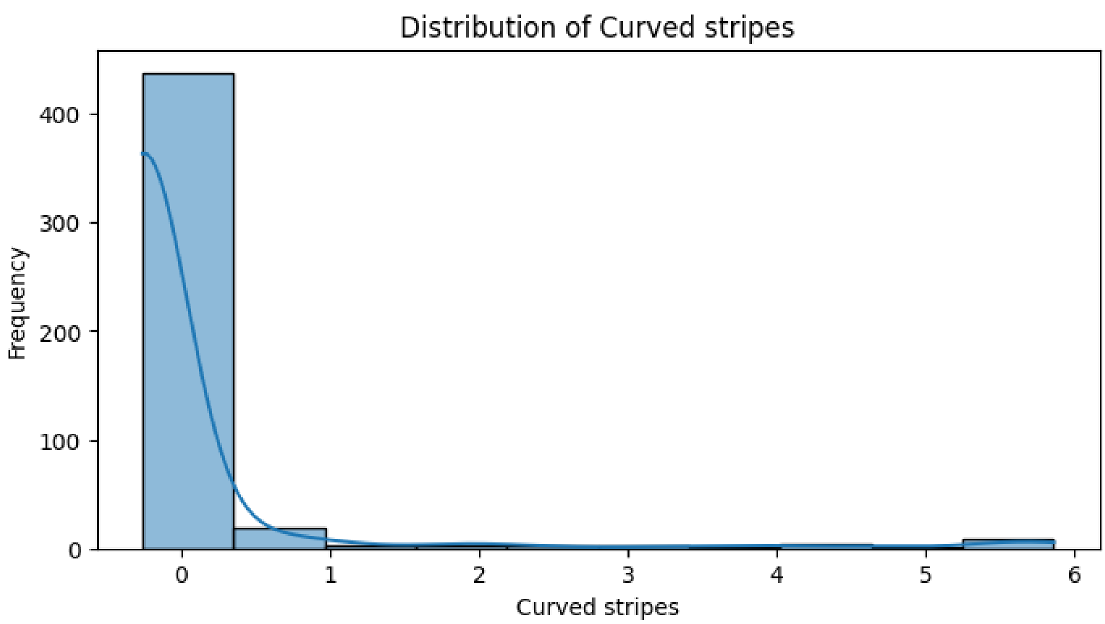

Distribution of Pegmatitic texture
Frequency
Pegmatitic texture
0
10
20
30
40
50
60
70
80
−1
0
1
2
3
4

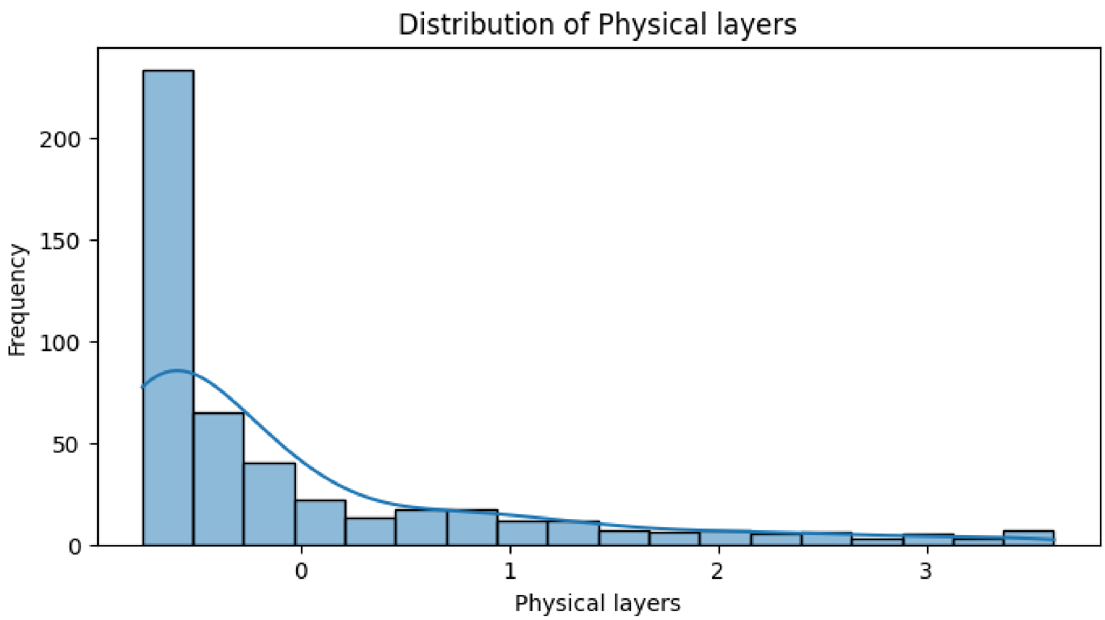

Distribution of Conchoidal fracture
Frequency
Conchoidal fracture
0
10
20
30
40
50
60
70
80
−1
0
1
2
3
4

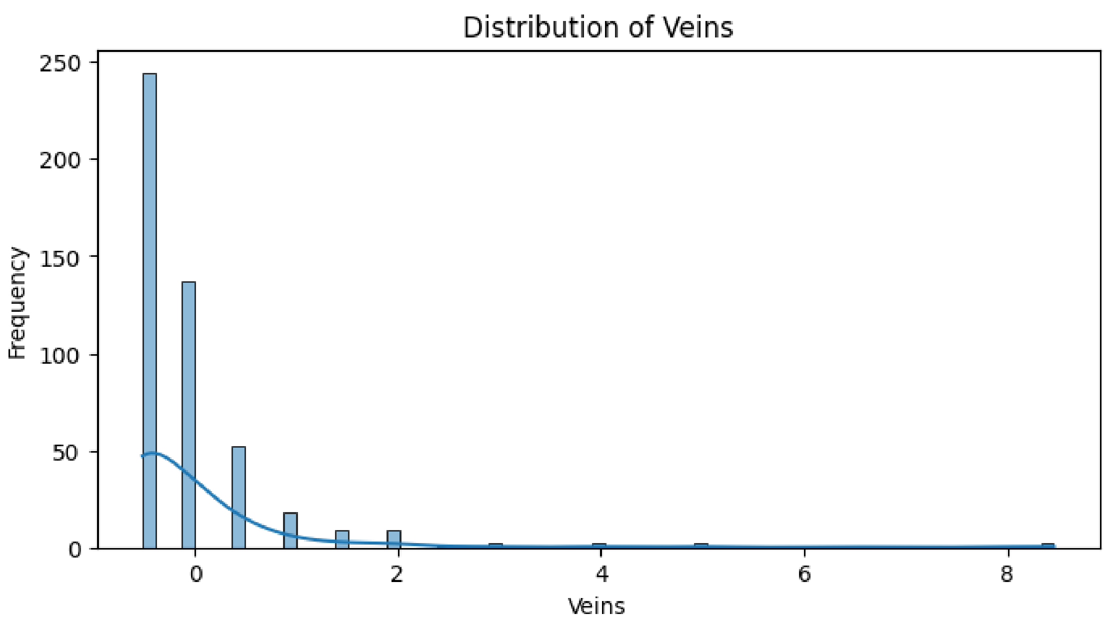

Distribution of Angular fragments
Frequency
350
300
250
200
150
100
50
0
0
1
2
3
4
Angular fragments

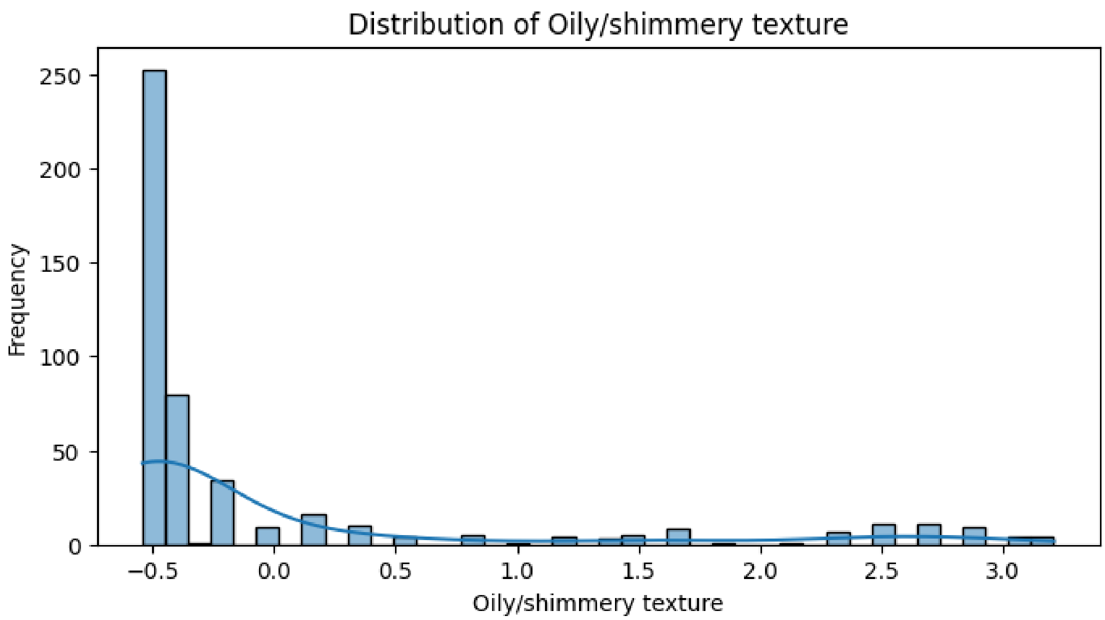

Distribution of Rounded fragments
Frequency
300
250
200
150
100
50
0
0
1
2
3
4
5
Rounded fragments

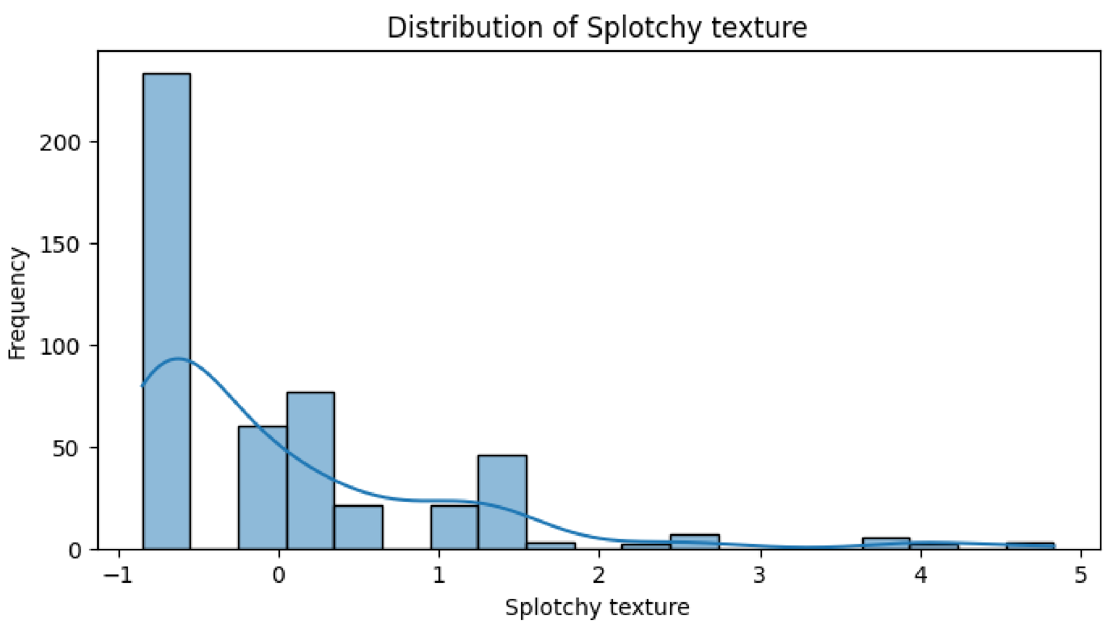

Distribution of Straight stripes
Frequency
0
50
100
150
200
250
300
350
400
0
1
2
3
4
5
Straight stripes

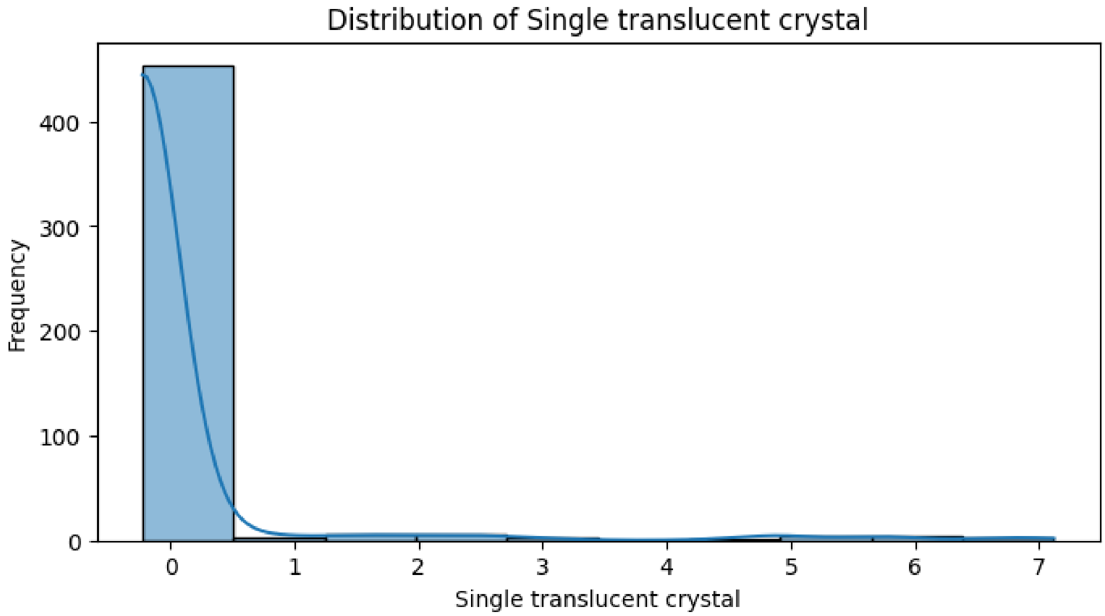

Distribution of Curved stripes
Frequency
0
100
200
300
400
0
1
2
3
4
5
6
Curved stripes

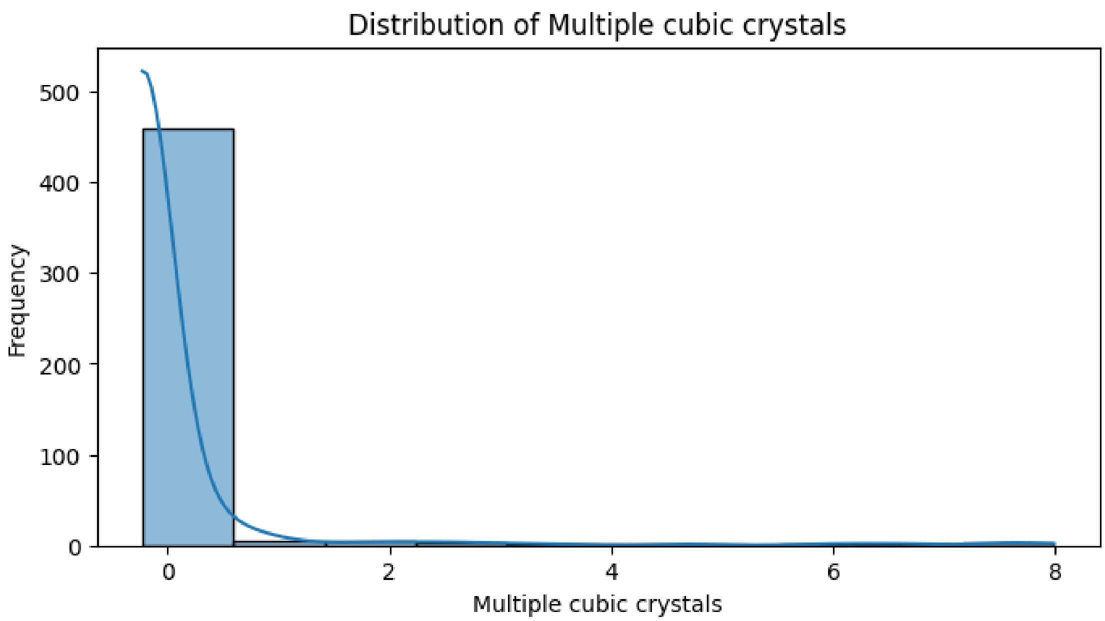

Distribution of Physical layers
Frequency
Physical layers
0
50
100
150
200
0
1
2
3

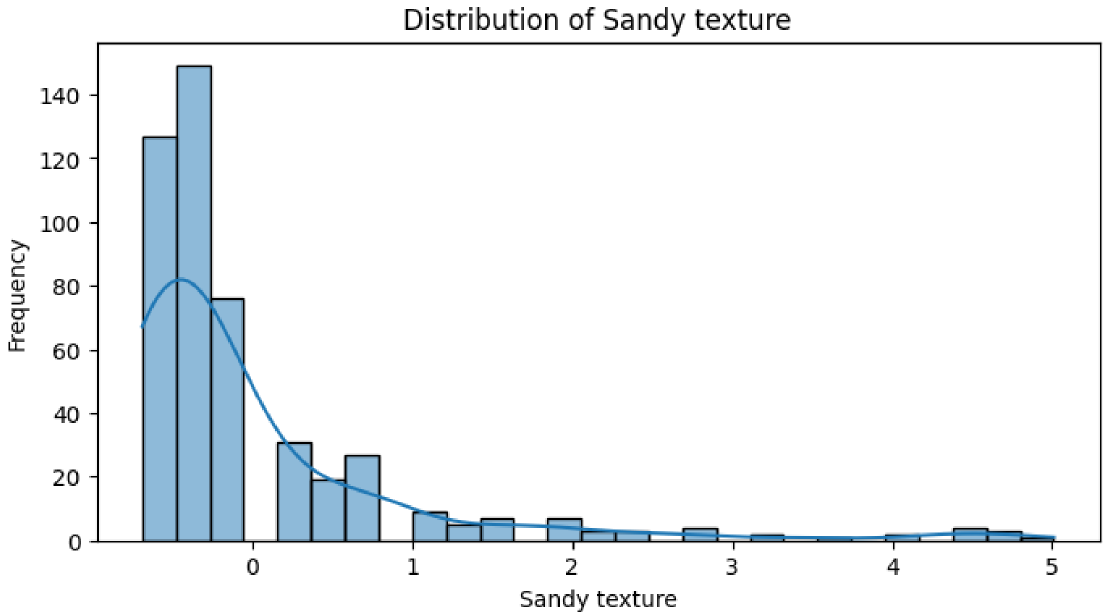

Distribution of Veins
Frequency
Veins
0
50
100
150
200
250
0
2
4
6
8

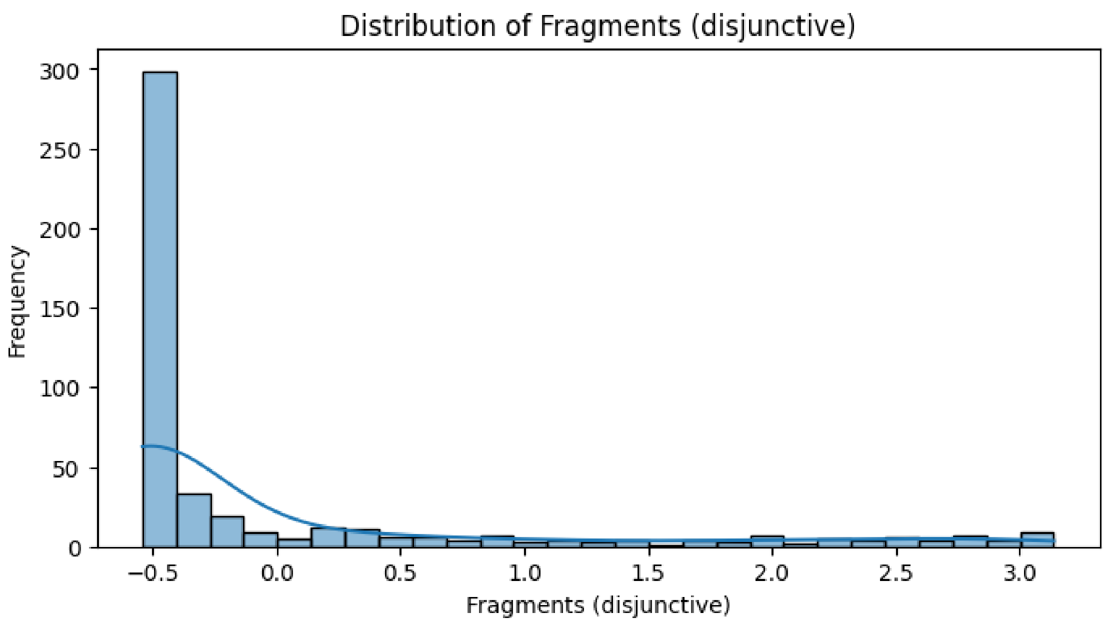

Distribution of Oily/shimmery texture
Frequency
250
200
150
100
50
0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Oily/shimmery texture

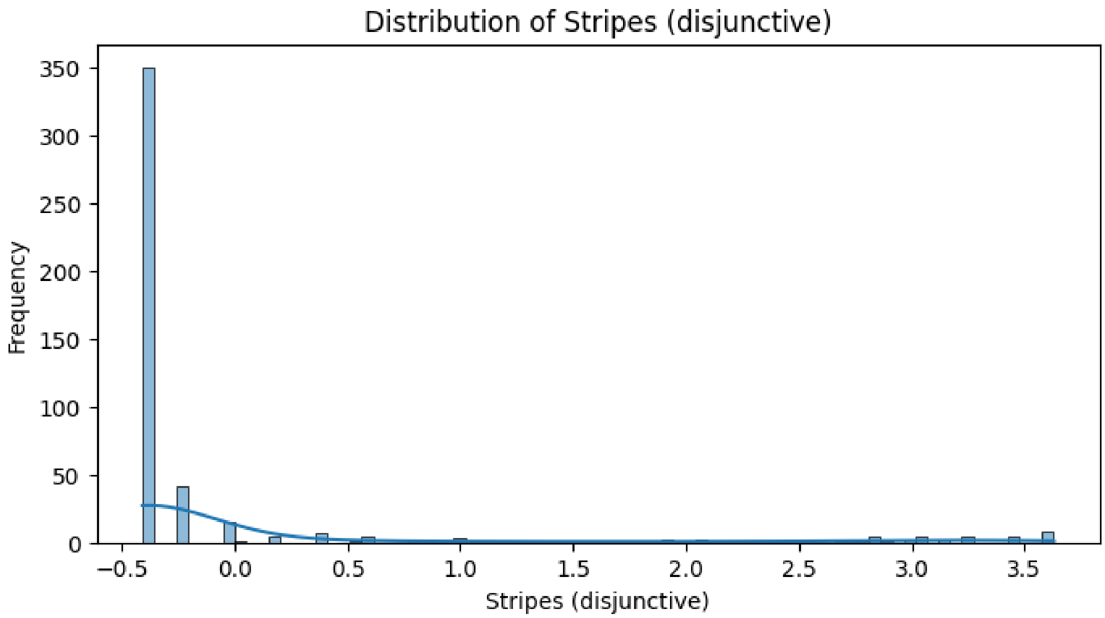

Distribution of Splotchy texture
Frequency
200
150
100
50
0
−1
0
1
2
3
4
5
Splotchy texture

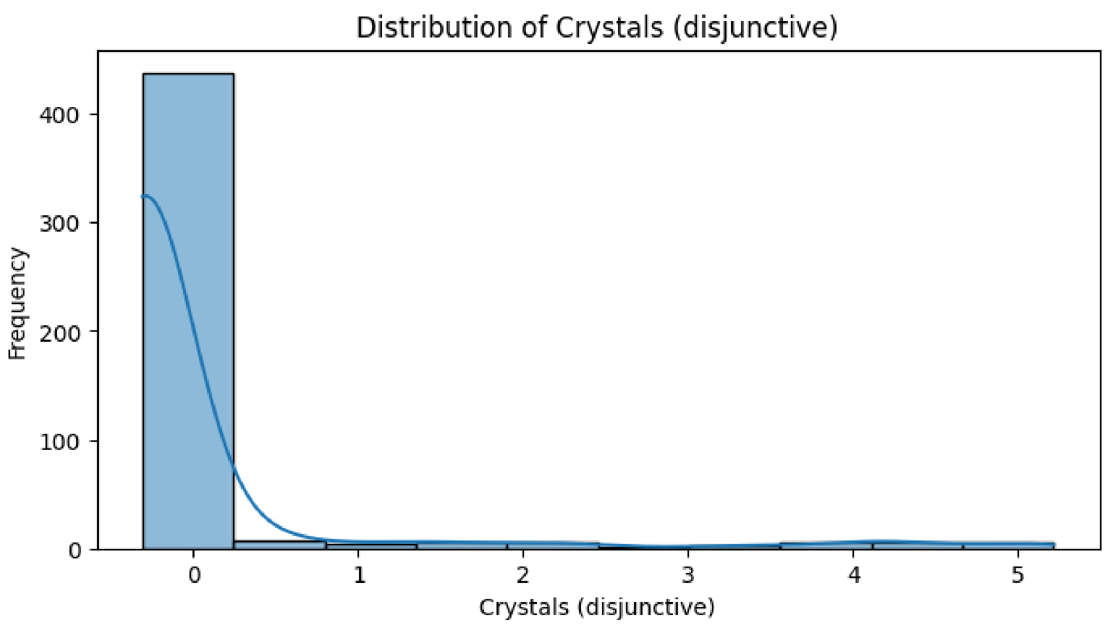

Distribution of Single translucent crystal
Frequency
0
100
200
300
400
0
1
2
3
4
5
6
7
Single translucent crystal


Distribution of Multiple cubic crystals
Frequency
0
100
200
300
400
500
0
2
4
6
8
Multiple cubic crystals


Distribution of Sandy texture
Frequency
Sandy texture
0
20
40
60
80
100
120
140
0
1
2
3
4
5


Distribution of Fragments (disjunctive)
Frequency
Fragments (disjunctive)
0
50
100
150
200
250
300
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0





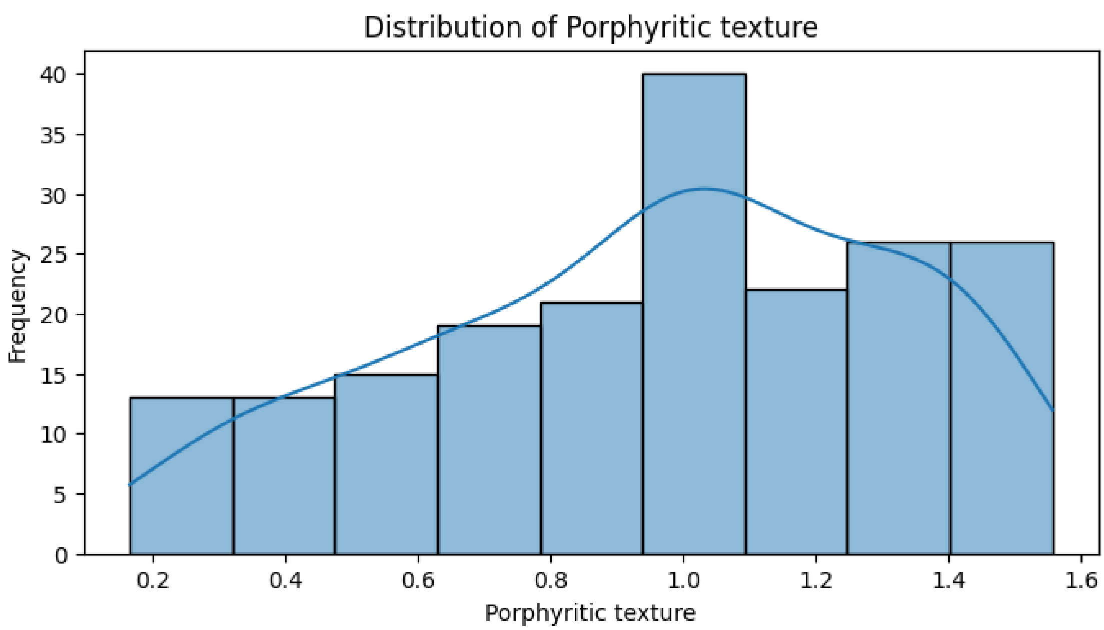
From looking at the histograms, we can see that all the attributes are mostly stretching to the right, which means they are right-skewed. Some attributes, like the angular and rounded fragments, as well as the veins, show similar kinds of patterns in how they spread out. On the other hand, attributes like crystals and stripes, along with multiple cubic and single translucent crystals, have a lot of small values but hardly any large ones when you look at how often they come up.

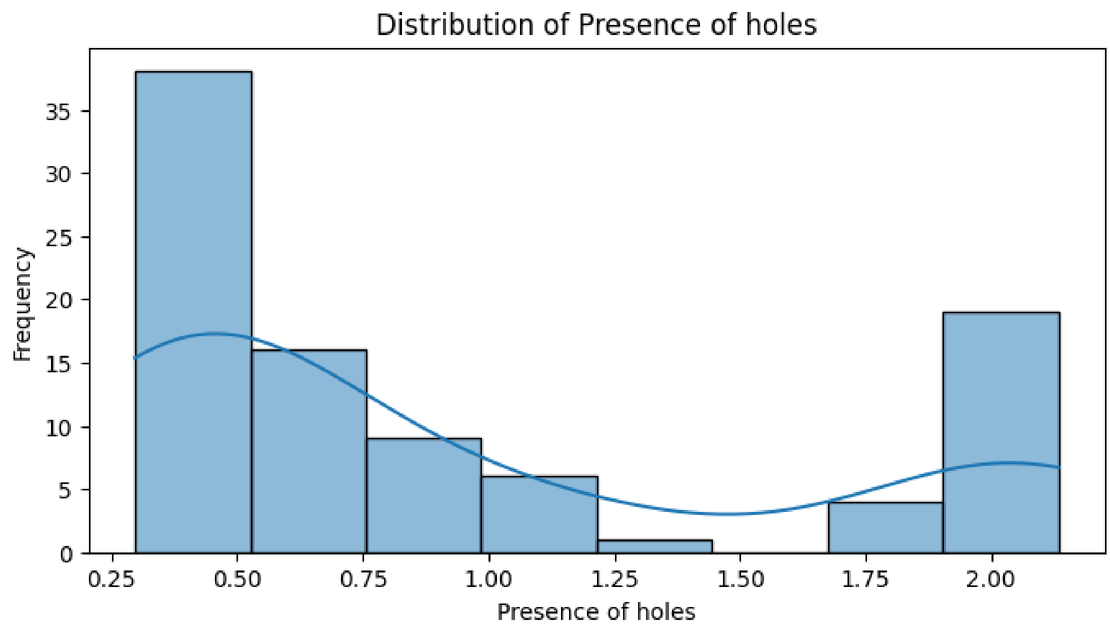
Tried to fix this skewness by using a square root change on the attributes. We chose this method because we wanted to make the spread of the attributes more even, especially since they were so heavily right-skewed.

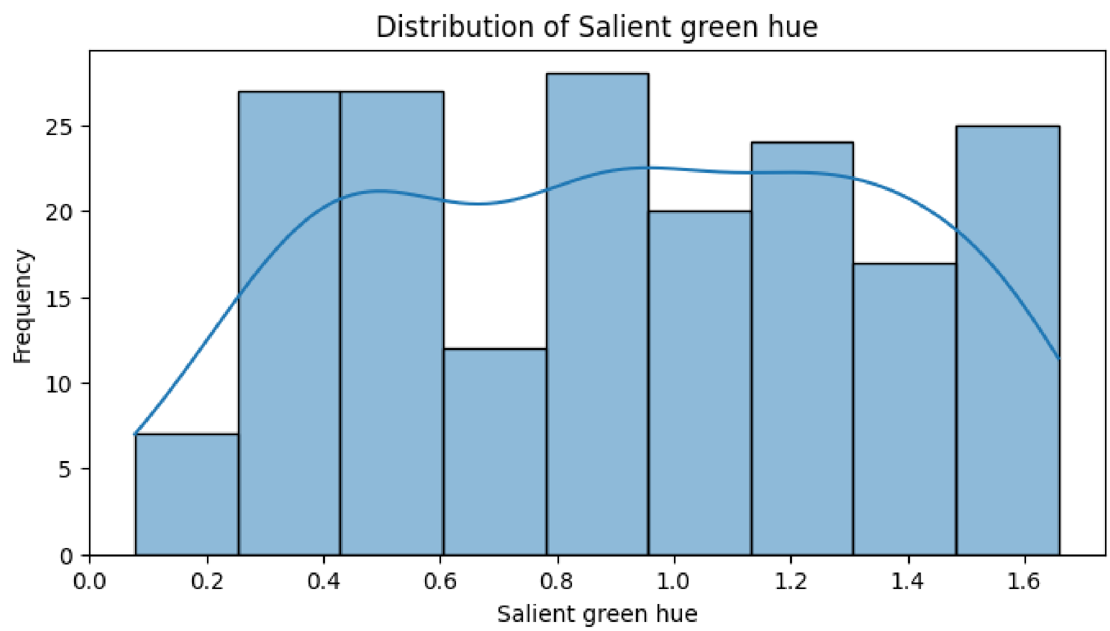
[8]:
```
import numpy as np

# Create a list of column names (attributes) in your dataset
attribute_data_columns = attribute_data.columns

# Apply a square root transformation to each attribute
for attr in attribute_data_columns:
    # Check if the attribute is numeric (e.g., not a label)
    if np.issubdtype(attribute_data[attr].dtype, np.number):
        attribute_data[attr] = np.sqrt(attribute_data[attr])
```

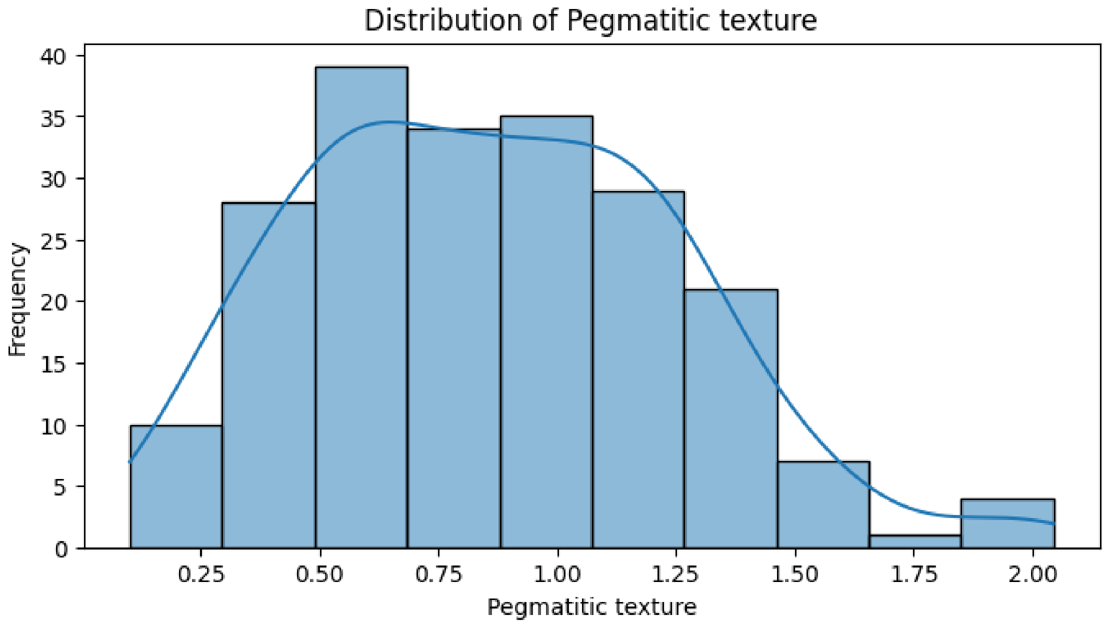
```
C:\Users\WELCOME\AppData\Local\Programs\Python\Python311\Lib\site-
packages\pandas\core\arraylike.py:396: RuntimeWarning: invalid value encountered
in sqrt
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

[9]:
```
# Plot histograms for each attribute
for column in attribute_data.columns:
    plt.figure(figsize=(8, 4))
    sns.histplot(attribute_data[column], kde=True)
    plt.title(f'Distribution of {column}')
    plt.xlabel(column)
    plt.ylabel("Frequency")
    plt.show()
```

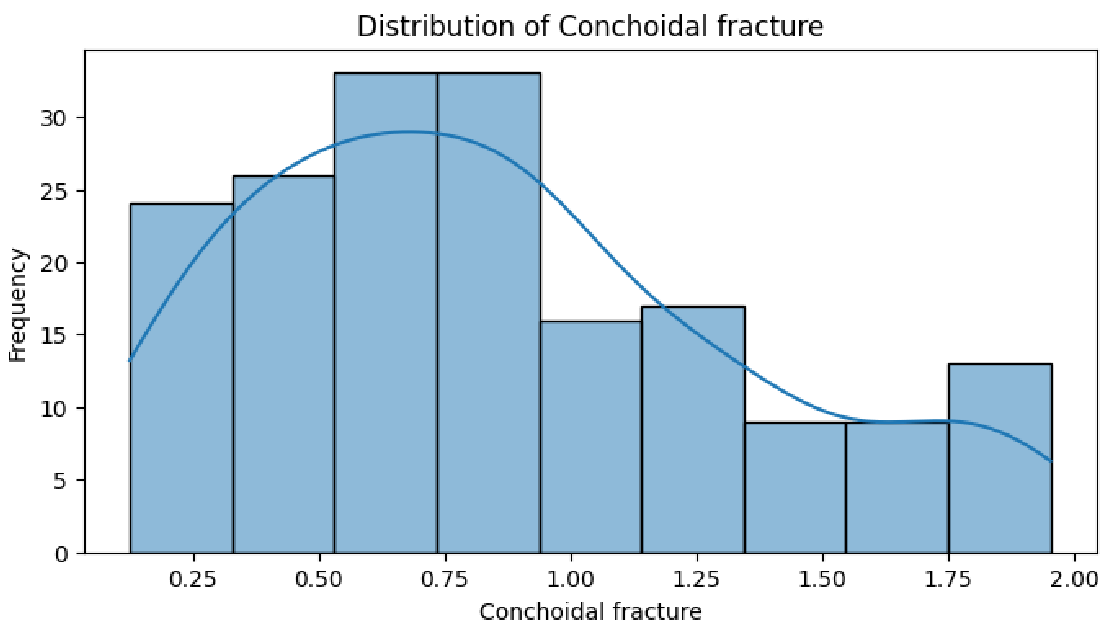



Distribution of Presence of holes
Frequency
Presence of holes
0
5
10
15
20
25
30
35
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

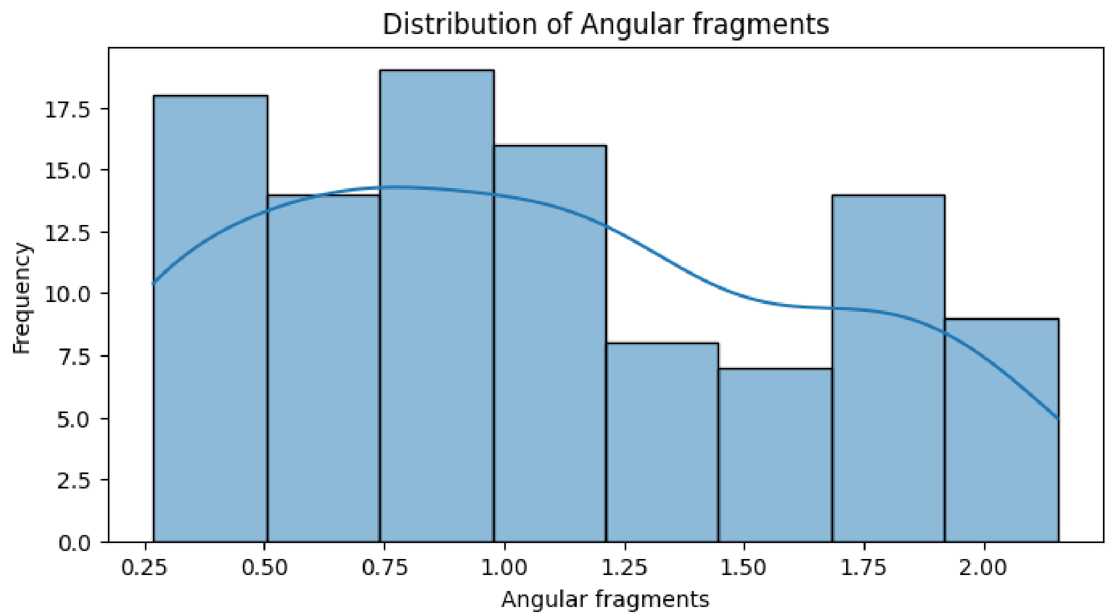

Distribution of Salient green hue
Frequency
Salient green hue
0
5
10
15
20
25
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6

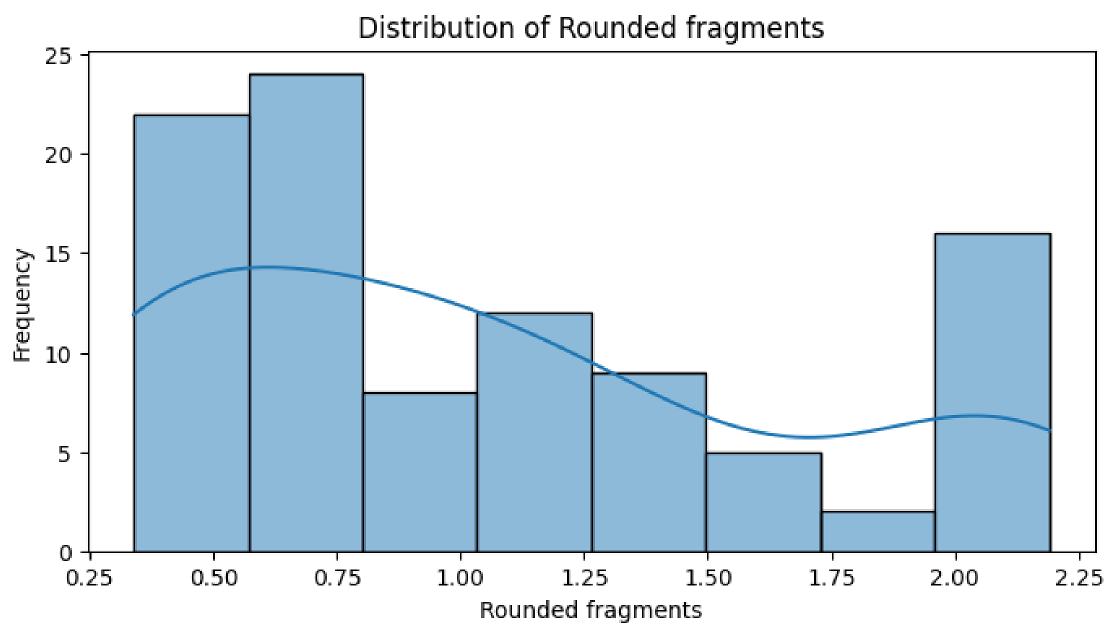


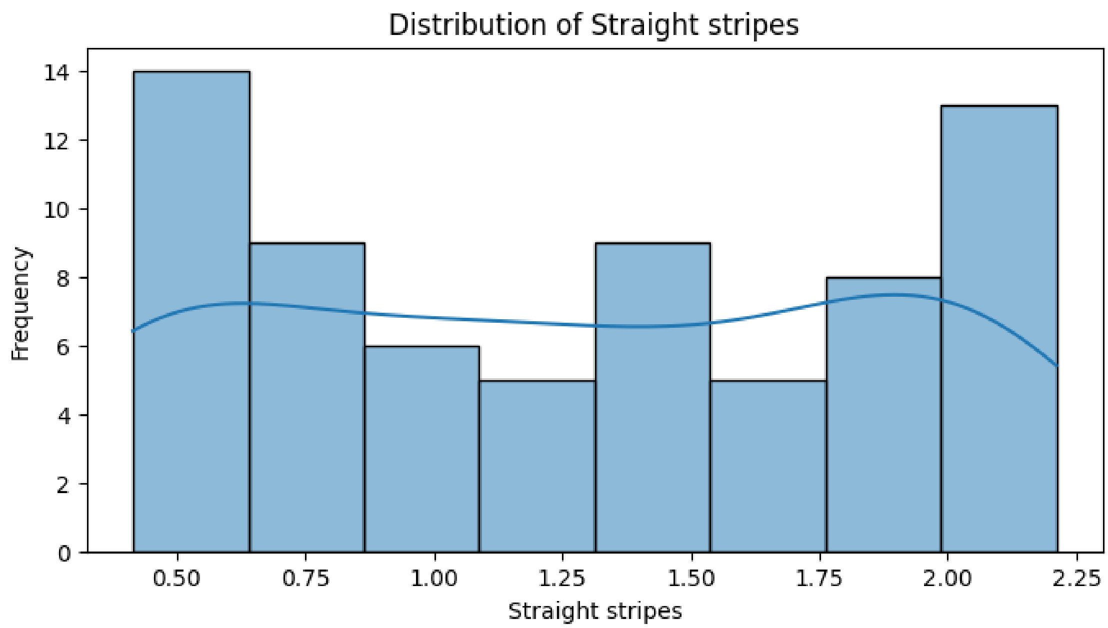
Distribution of Pegmatitic texture
Frequency
Pegmatitic texture
0
5
10
15
20
25
30
35
40
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

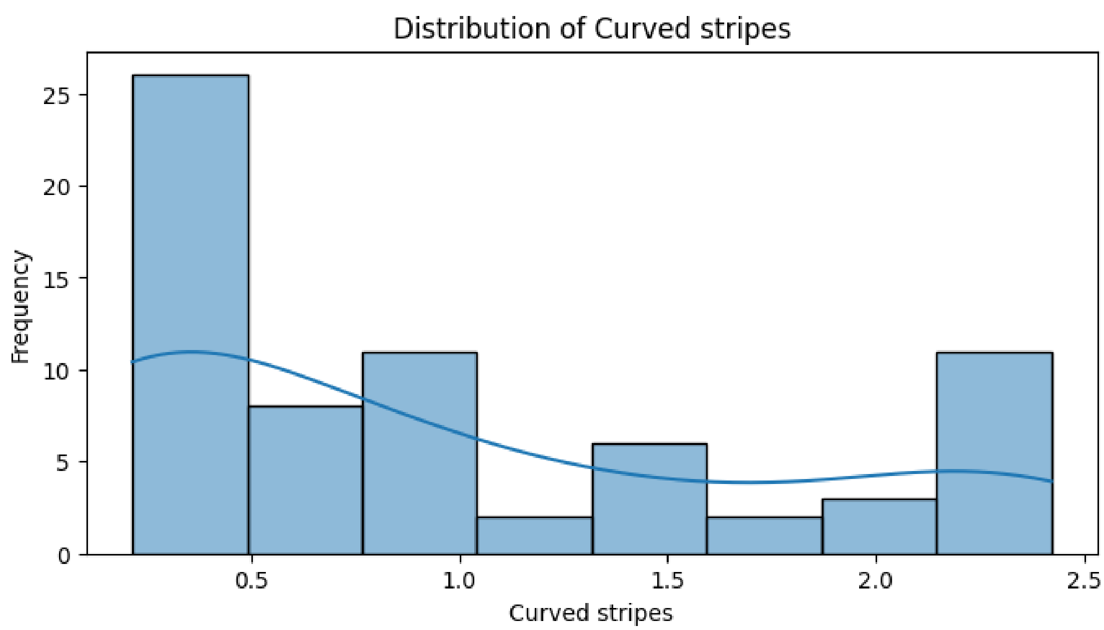


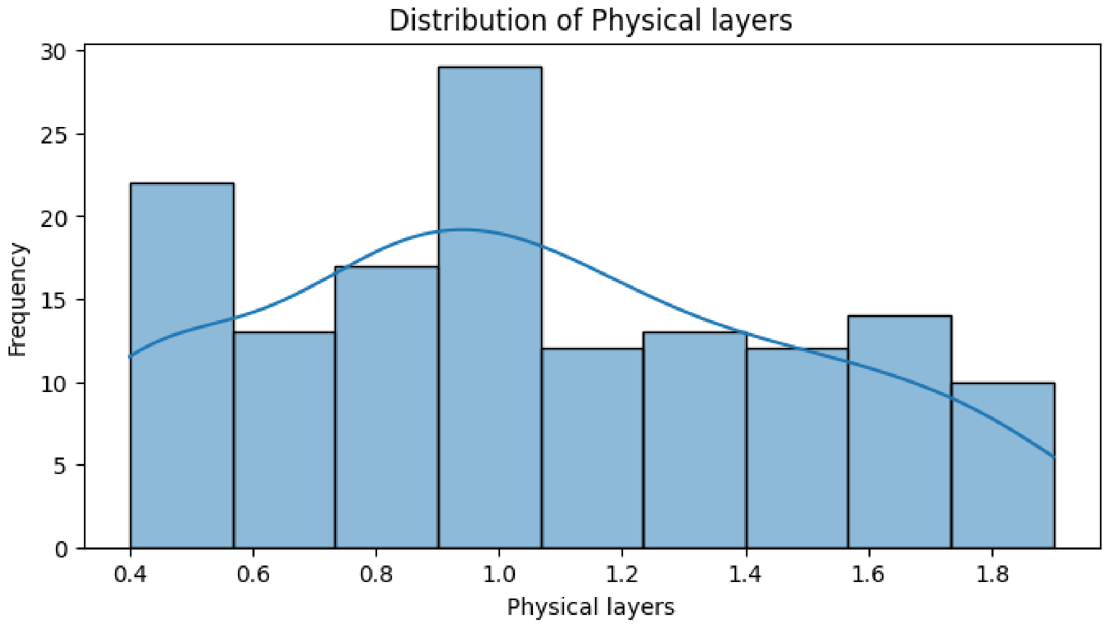
Distribution of Conchoidal fracture
Frequency
Conchoidal fracture
0
5
10
15
20
25
30
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

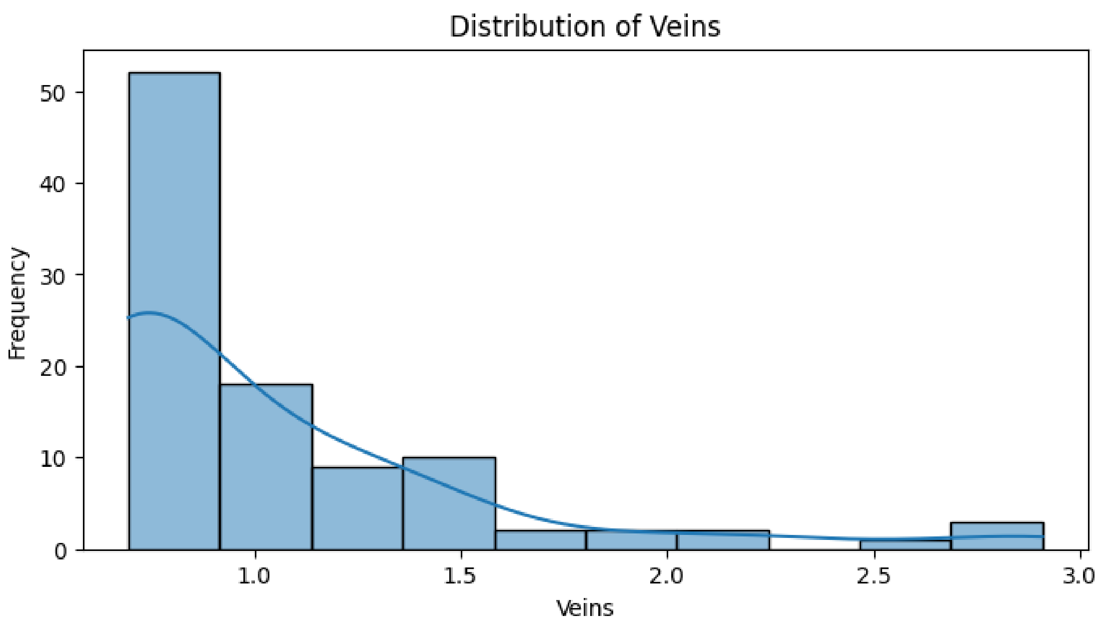

Distribution of Angular fragments
Frequency
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Angular fragments

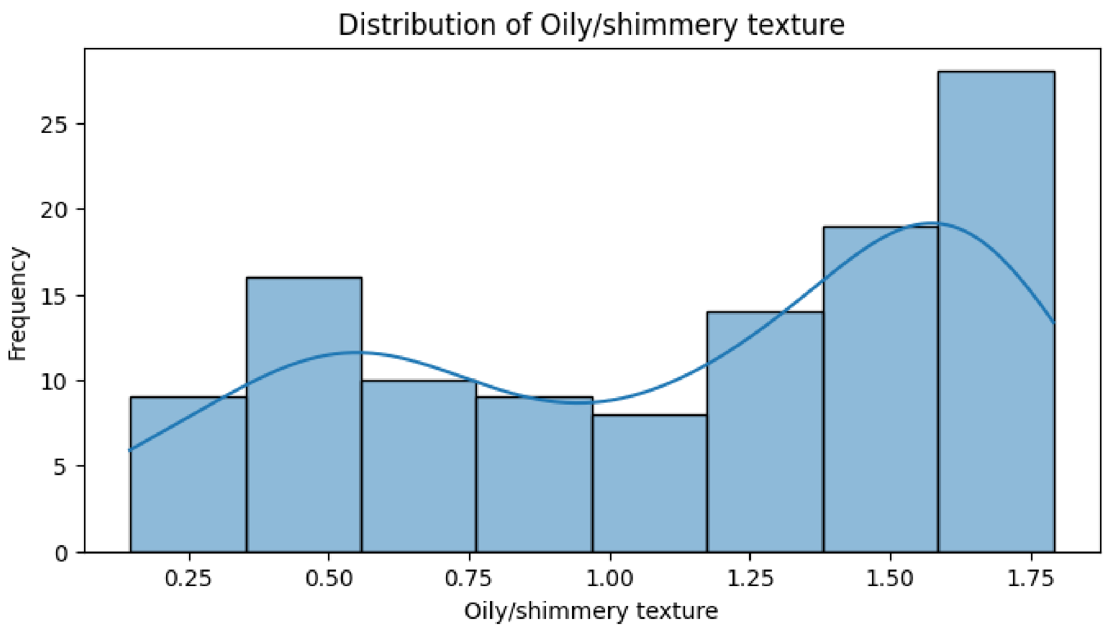

Distribution of Rounded fragments
Frequency
0
5
10
15
20
25
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.25
Rounded fragments

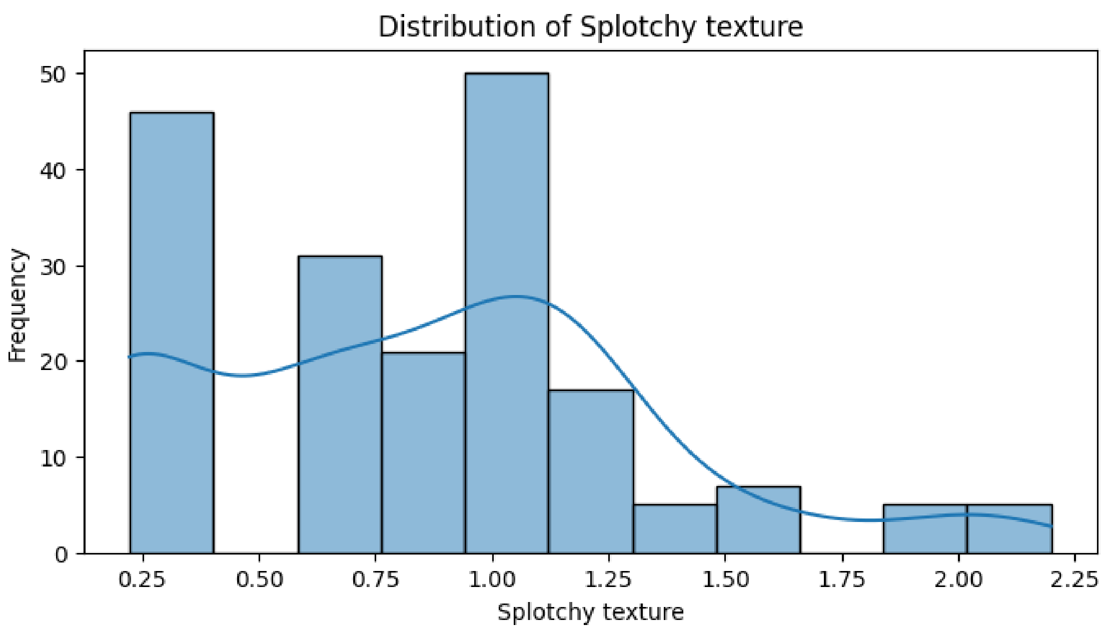

Distribution of Straight stripes
Frequency
0
2
4
6
8
10
12
14
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.25
Straight stripes

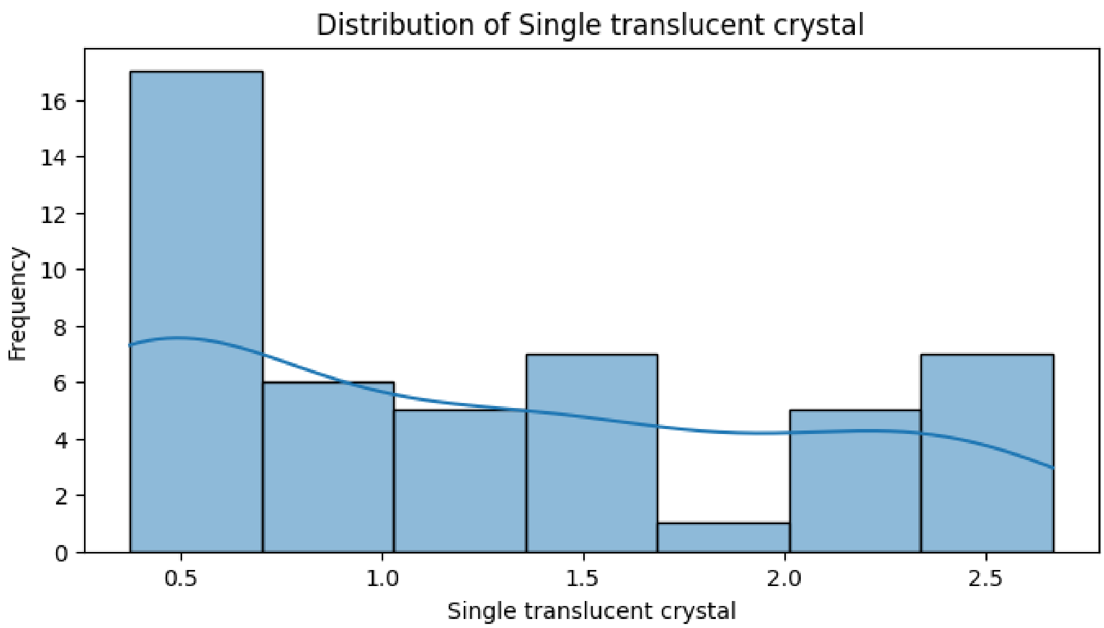

Distribution of Curved stripes
Frequency
0
5
10
15
20
25
0.5
1.0
1.5
2.0
2.5
Curved stripes


Distribution of Physical layers
Frequency
Physical layers
0
5
10
15
20
25
30
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1.8

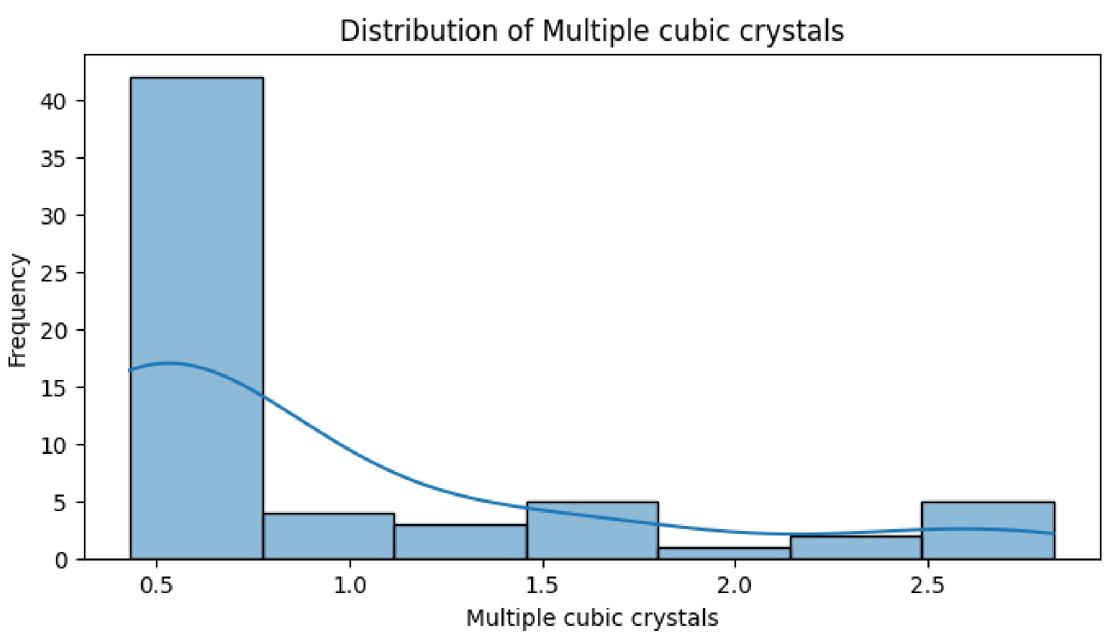

Distribution of Veins
Frequency
Veins
0
10
20
30
40
50
1.0
1.5
2.0
2.5
3.0


Distribution of Oily/shimmery texture
Frequency
0
5
10
15
20
25
0.25
0.50
0.75
1.00
1.25
1.50
1.75
Oily/shimmery texture

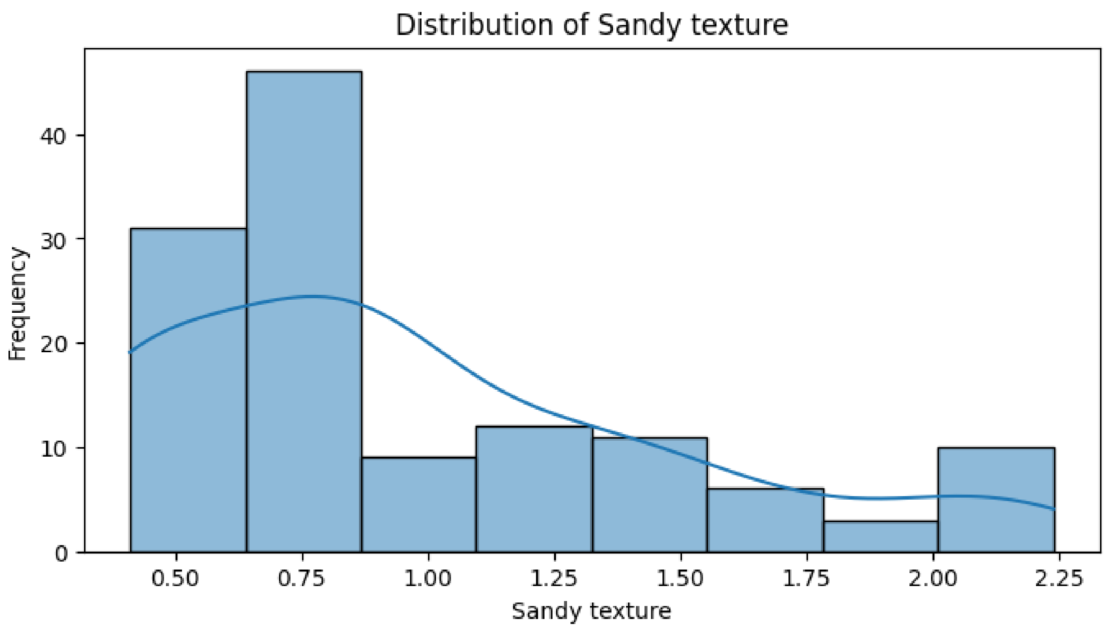

Distribution of Splotchy texture
Frequency
0
10
20
30
40
50
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.25
Splotchy texture



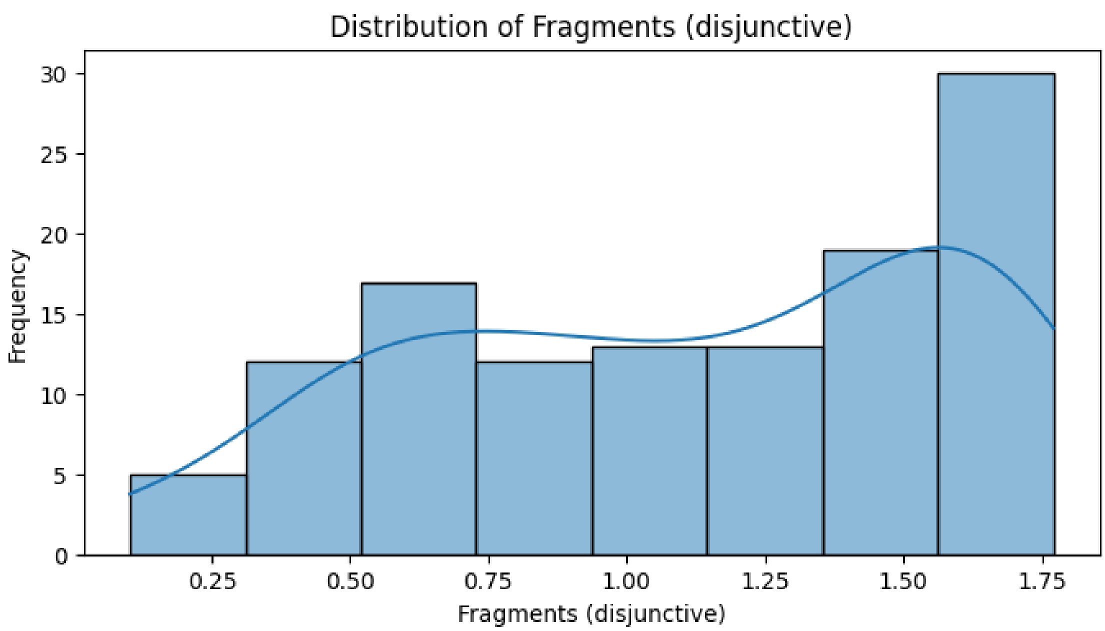
Distribution of Single translucent crystal
Frequency
Single translucent crystal
0
2
4
6
8
10
12
14
16
0.5
1.0
1.5
2.0
2.5



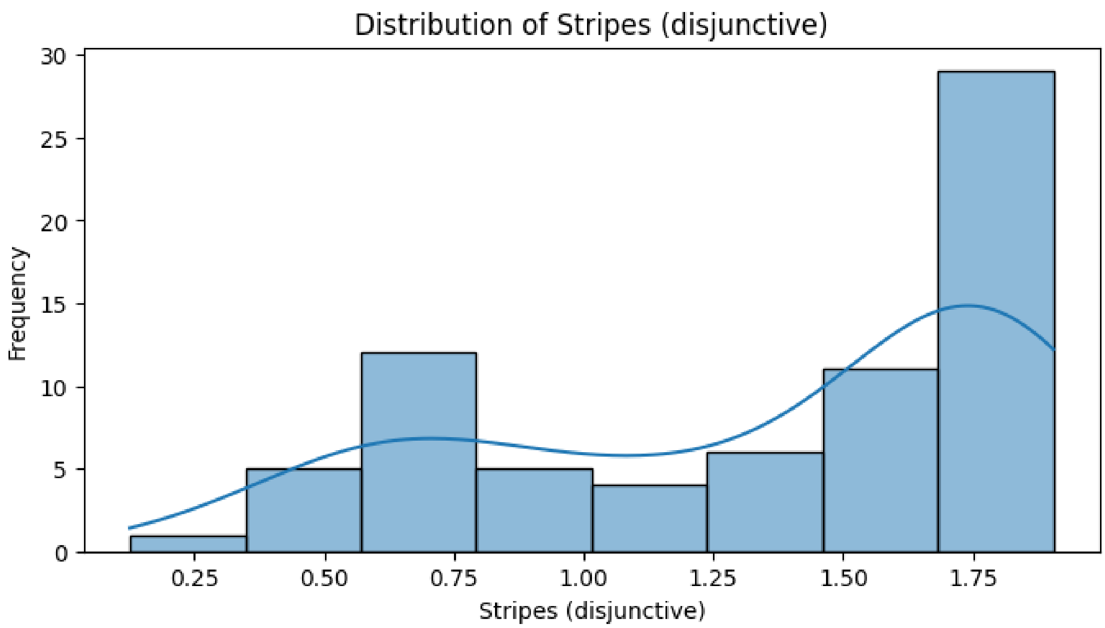
Distribution of Multiple cubic crystals
Frequency
Multiple cubic crystals
0
5
10
15
20
25
30
35
40
0.5
1.0
1.5
2.0
2.5

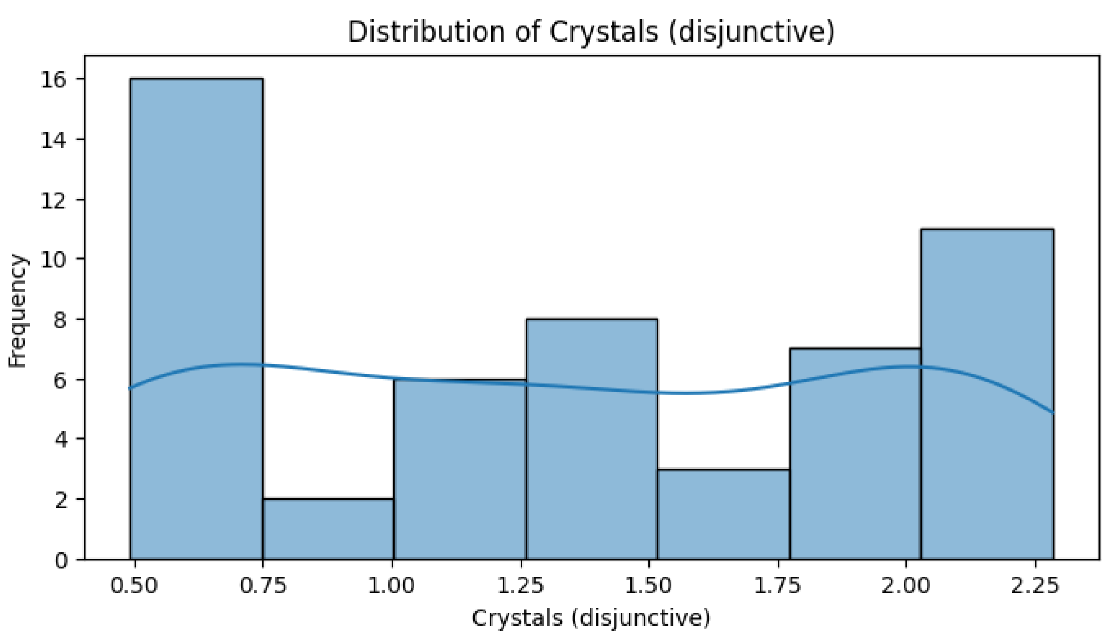


Distribution of Sandy texture
Frequency
Sandy texture
0
10
20
30
40
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.25



Distribution of Fragments (disjunctive)
Frequency
Fragments (disjunctive)
0
5
10
15
20
25
30
0.25
0.50
0.75
1.00
1.25
1.50
1.75





The skewness is removed by applying Square root transform

[10]:
```
attribute_data.isnull().sum()
```

[10]:
```
Porphyritic texture          285
Presence of holes            387
Salient green hue            293
Pegmatitic texture           272
Conchoidal fracture          300
Angular fragments            375
Rounded fragments            382
Straight stripes             411
Curved stripes               411
Physical layers              338
Veins                        381
Oily/shimmery texture        367
Splotchy texture             293
Single translucent crystal   432
Multiple cubic crystals      418
Sandy texture                352
Fragments (disjunctive)      359
Stripes (disjunctive)        407
Crystals (disjunctive)       427
dtype: int64
```

Analysing and discuss the relationships between the data attributes and between the data attributes and labels. This involves computing the Pearson Correlation Coefficient (PCC) and generating scatter plots

[11]:
```python
correlation_matrix = attribute_data.corr()
print(correlation_matrix)
# Generate scatter plots for key attribute pairs
sns.pairplot(attribute_data)
plt.show()
```

```
                            Porphyritic texture  Presence of holes  \
Porphyritic texture                    1.000000          -0.181601
Presence of holes                     -0.181601           1.000000
Salient green hue                      0.205400          -0.008385
Pegmatitic texture                     0.146925          -0.047175
Conchoidal fracture                    0.062225          -0.291075
Angular fragments                      0.464689          -0.122688
Rounded fragments                      0.544725          -0.298588
Straight stripes                      -0.090426           0.713204
Curved stripes                        -0.390138          -0.882783
Physical layers                       -0.854029          -0.364786
Veins                                 -0.091997                NaN
Oily/shimmery texture                  0.013736          -0.440973
Splotchy texture                      -0.210356          -0.223379
Single translucent crystal             0.059161          -1.000000
Multiple cubic crystals               -0.453815           0.362936
Sandy texture                         -0.363811          -0.214095
```

Fragments (disjunctive)	0.694560	-0.115875
Stripes (disjunctive)	-0.229228	0.450846
Crystals (disjunctive)	-0.586914	-0.091124

	Salient green hue	Pegmatitic texture \
Porphyritic texture	0.205400	0.146925
Presence of holes	-0.008385	-0.047175
Salient green hue	1.000000	0.045326
Pegmatitic texture	0.045326	1.000000
Conchoidal fracture	-0.028137	-0.162763
Angular fragments	0.089501	0.020349
Rounded fragments	0.001050	0.172993
Straight stripes	-0.179423	-0.420904
Curved stripes	-0.056188	-0.345259
Physical layers	-0.247542	0.036484
Veins	-0.030061	-0.111310
Oily/shimmery texture	-0.202921	-0.323804
Splotchy texture	-0.084205	-0.256783
Single translucent crystal	-0.543265	-0.361574
Multiple cubic crystals	-0.115566	0.225359
Sandy texture	-0.150152	-0.335719
Fragments (disjunctive)	0.105762	0.140796
Stripes (disjunctive)	-0.149615	-0.688255
Crystals (disjunctive)	-0.556113	0.034766

	Conchoidal fracture	Angular fragments \
Porphyritic texture	0.062225	0.464689
Presence of holes	-0.291075	-0.122688
Salient green hue	-0.028137	0.089501
Pegmatitic texture	-0.162763	0.020349
Conchoidal fracture	1.000000	-0.126731
Angular fragments	-0.126731	1.000000
Rounded fragments	-0.482527	-0.153708
Straight stripes	-0.284143	-0.273148
Curved stripes	-0.259150	0.234508
Physical layers	-0.268292	-0.376744
Veins	-0.074132	-0.649544
Oily/shimmery texture	0.465135	-0.508341
Splotchy texture	-0.008356	-0.347510
Single translucent crystal	-0.212238	1.000000
Multiple cubic crystals	-0.145163	-0.127619
Sandy texture	-0.196974	-0.488482
Fragments (disjunctive)	-0.382982	0.685520
Stripes (disjunctive)	-0.298599	-0.975556
Crystals (disjunctive)	-0.274594	-0.203835

	Rounded fragments	Straight stripes \
Porphyritic texture	0.544725	-0.090426

Presence of holes	-0.298588	0.713204
Salient green hue	0.001050	-0.179423
Pegmatitic texture	0.172993	-0.420904
Conchoidal fracture	-0.482527	-0.284143
Angular fragments	-0.153708	-0.273148
Rounded fragments	1.000000	NaN
Straight stripes	NaN	1.000000
Curved stripes	0.183589	-0.427620
Physical layers	-0.156671	-0.328523
Veins	0.650269	0.152600
Oily/shimmery texture	0.006354	-0.035397
Splotchy texture	-0.517974	0.064573
Single translucent crystal	-1.000000	-0.605092
Multiple cubic crystals	-0.242109	-0.549232
Sandy texture	-0.444239	-0.094047
Fragments (disjunctive)	0.659817	0.787314
Stripes (disjunctive)	NaN	0.754480
Crystals (disjunctive)	0.278345	0.219075

	Curved stripes	Physical layers	Veins \
Porphyritic texture	-0.390138	-0.854029	-0.091997
Presence of holes	-0.882783	-0.364786	NaN
Salient green hue	-0.056188	-0.247542	-0.030061
Pegmatitic texture	-0.345259	0.036484	-0.111310
Conchoidal fracture	-0.259150	-0.268292	-0.074132
Angular fragments	0.234508	-0.376744	-0.649544
Rounded fragments	0.183589	-0.156671	0.650269
Straight stripes	-0.427620	-0.328523	0.152600
Curved stripes	1.000000	-0.277384	-0.062625
Physical layers	-0.277384	1.000000	-0.191052
Veins	-0.062625	-0.191052	1.000000
Oily/shimmery texture	-0.227129	-0.182128	0.020681
Splotchy texture	-0.221643	-0.133042	-0.251296
Single translucent crystal	-0.387456	-0.382353	-0.028522
Multiple cubic crystals	NaN	-0.090518	0.728863
Sandy texture	-0.297645	-0.236198	-0.152459
Fragments (disjunctive)	0.031828	-0.251886	0.013013
Stripes (disjunctive)	0.460361	-0.426823	-0.053723
Crystals (disjunctive)	-1.000000	-0.162053	-0.051784

	Oily/shimmery texture	Splotchy texture \
Porphyritic texture	0.013736	-0.210356
Presence of holes	-0.440973	-0.223379
Salient green hue	-0.202921	-0.084205
Pegmatitic texture	-0.323804	-0.256783
Conchoidal fracture	0.465135	-0.008356
Angular fragments	-0.508341	-0.347510
Rounded fragments	0.006354	-0.517974

Straight stripes	-0.035397	0.064573
Curved stripes	-0.227129	-0.221643
Physical layers	-0.182128	-0.133042
Veins	0.020681	-0.251296
Oily/shimmery texture	1.000000	-0.013358
Splotchy texture	-0.013358	1.000000
Single translucent crystal	-0.441816	-0.109616
Multiple cubic crystals	-0.417975	-0.577366
Sandy texture	-0.484977	-0.311917
Fragments (disjunctive)	-0.365708	-0.426579
Stripes (disjunctive)	-0.190696	0.425135
Crystals (disjunctive)	-0.419929	0.048581

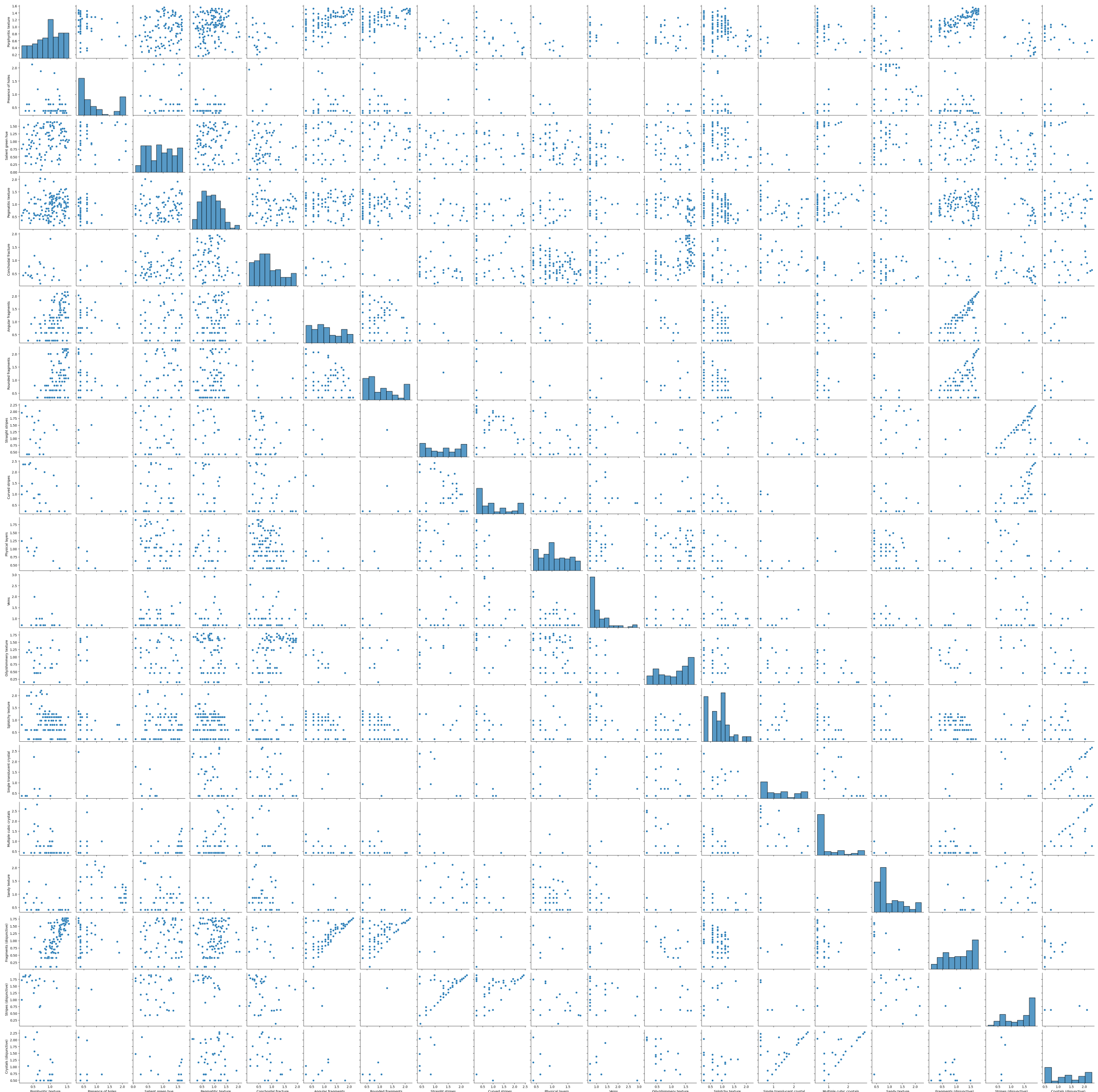
	Single translucent crystal \
Porphyritic texture	0.059161
Presence of holes	-1.000000
Salient green hue	-0.543265
Pegmatitic texture	-0.361574
Conchoidal fracture	-0.212238
Angular fragments	1.000000
Rounded fragments	-1.000000
Straight stripes	-0.605092
Curved stripes	-0.387456
Physical layers	-0.382353
Veins	-0.028522
Oily/shimmery texture	-0.441816
Splotchy texture	-0.109616
Single translucent crystal	1.000000
Multiple cubic crystals	-0.634150
Sandy texture	NaN
Fragments (disjunctive)	0.622262
Stripes (disjunctive)	-0.636307
Crystals (disjunctive)	0.505556

	Multiple cubic crystals	Sandy texture \
Porphyritic texture	-0.453815	-0.363811
Presence of holes	0.362936	-0.214095
Salient green hue	-0.115566	-0.150152
Pegmatitic texture	0.225359	-0.335719
Conchoidal fracture	-0.145163	-0.196974
Angular fragments	-0.127619	-0.488482
Rounded fragments	-0.242109	-0.444239
Straight stripes	-0.549232	-0.094047
Curved stripes	NaN	-0.297645
Physical layers	-0.090518	-0.236198
Veins	0.728863	-0.152459
Oily/shimmery texture	-0.417975	-0.484977
Splotchy texture	-0.577366	-0.311917

Single translucent crystal	-0.634150	NaN
Multiple cubic crystals	1.000000	-0.500000
Sandy texture	-0.500000	1.000000
Fragments (disjunctive)	-0.209574	-0.488427
Stripes (disjunctive)	NaN	-0.159306
Crystals (disjunctive)	0.714061	NaN

	Fragments (disjunctive)	Stripes (disjunctive) \
Porphyritic texture	0.694560	-0.229228
Presence of holes	-0.115875	0.450846
Salient green hue	0.105762	-0.149615
Pegmatitic texture	0.140796	-0.688255
Conchoidal fracture	-0.382982	-0.298599
Angular fragments	0.685520	-0.975556
Rounded fragments	0.659817	NaN
Straight stripes	0.787314	0.754480
Curved stripes	0.031828	0.460361
Physical layers	-0.251886	-0.426823
Veins	0.013013	-0.053723
Oily/shimmery texture	-0.365708	-0.190696
Splotchy texture	-0.426579	0.425135
Single translucent crystal	0.622262	-0.636307
Multiple cubic crystals	-0.209574	NaN
Sandy texture	-0.488427	-0.159306
Fragments (disjunctive)	1.000000	1.000000
Stripes (disjunctive)	1.000000	1.000000
Crystals (disjunctive)	0.073724	0.447979

	Crystals (disjunctive)
Porphyritic texture	-0.586914
Presence of holes	-0.091124
Salient green hue	-0.556113
Pegmatitic texture	0.034766
Conchoidal fracture	-0.274594
Angular fragments	-0.203835
Rounded fragments	0.278345
Straight stripes	0.219075
Curved stripes	-1.000000
Physical layers	-0.162053
Veins	-0.051784
Oily/shimmery texture	-0.419929
Splotchy texture	0.048581
Single translucent crystal	0.505556
Multiple cubic crystals	0.714061
Sandy texture	NaN
Fragments (disjunctive)	0.073724
Stripes (disjunctive)	0.447979
Crystals (disjunctive)	1.000000



PCC between label (rock category) and attributes

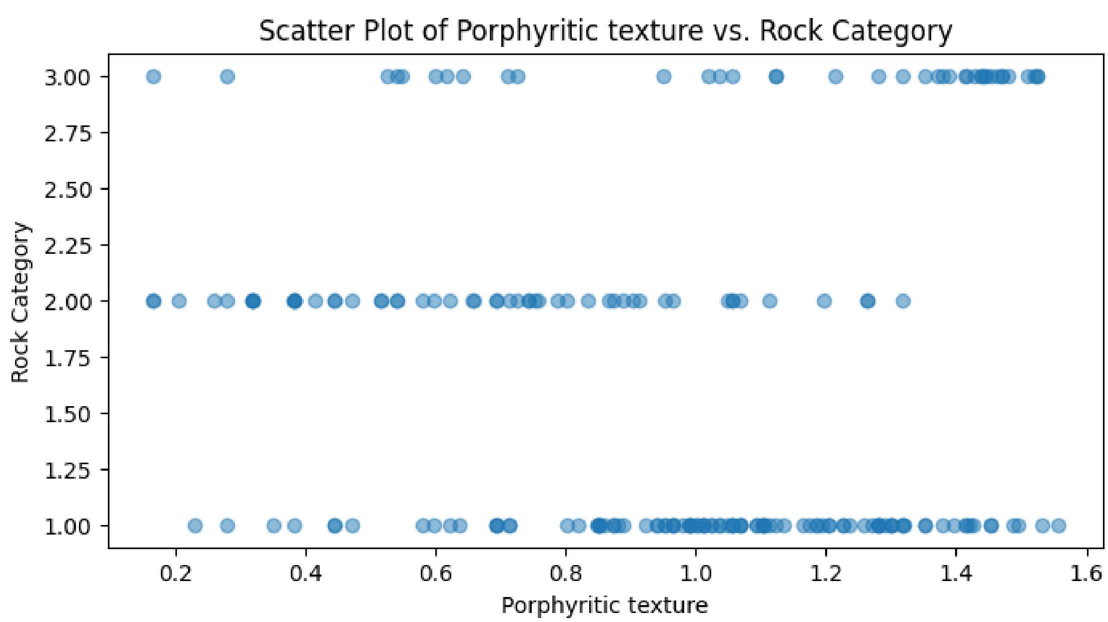
[12]:
```
correlation_matrix = pd.concat([rock_data, attribute_data], axis=1).corr()
correlation_with_label = correlation_matrix.iloc[0, 1:]

# Display PCC values for each attribute
print("Pearson Correlation Coefficients with Label:")
print(correlation_with_label)
```

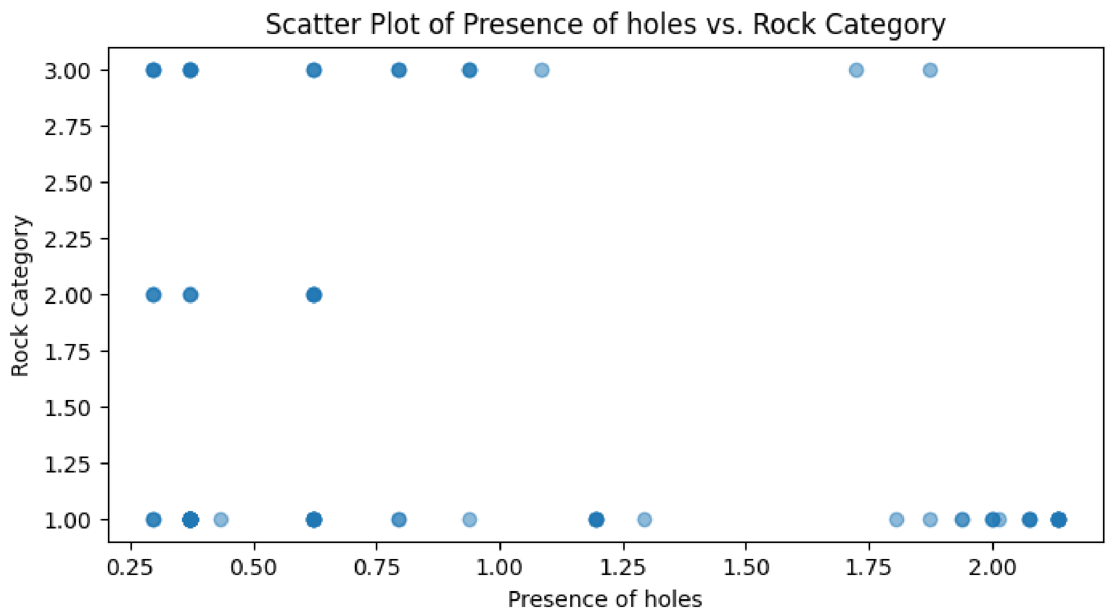
```
Pearson Correlation Coefficients with Label:
Porphyritic texture          -0.017944
Presence of holes            -0.272771
Salient green hue            -0.155960
Pegmatitic texture            0.024465
```

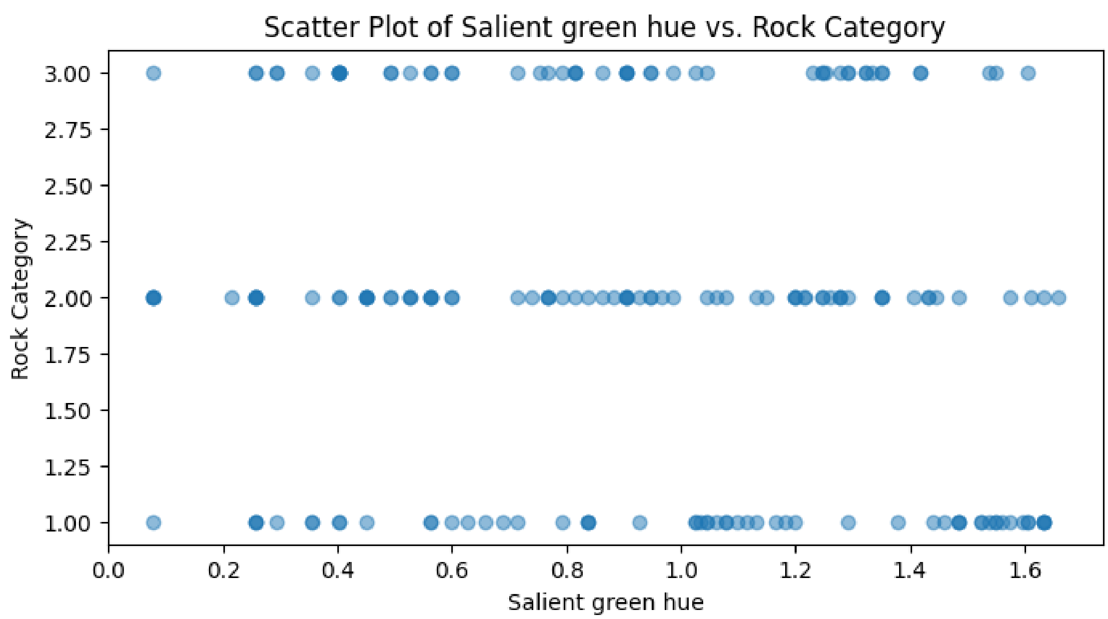
```
Conchoidal fracture          -0.146585
Angular fragments             0.262784
Rounded fragments             0.422041
Straight stripes              0.035009
Curved stripes               -0.142699
Physical layers              -0.039881
Veins                         0.065365
Oily/shimmery texture        -0.202985
Splotchy texture             -0.123487
Single translucent crystal    0.467668
Multiple cubic crystals       0.552165
Sandy texture                 0.301058
Fragments (disjunctive)       0.481428
Stripes (disjunctive)        -0.224850
Crystals (disjunctive)        0.658528
Name: rock category, dtype: float64
```

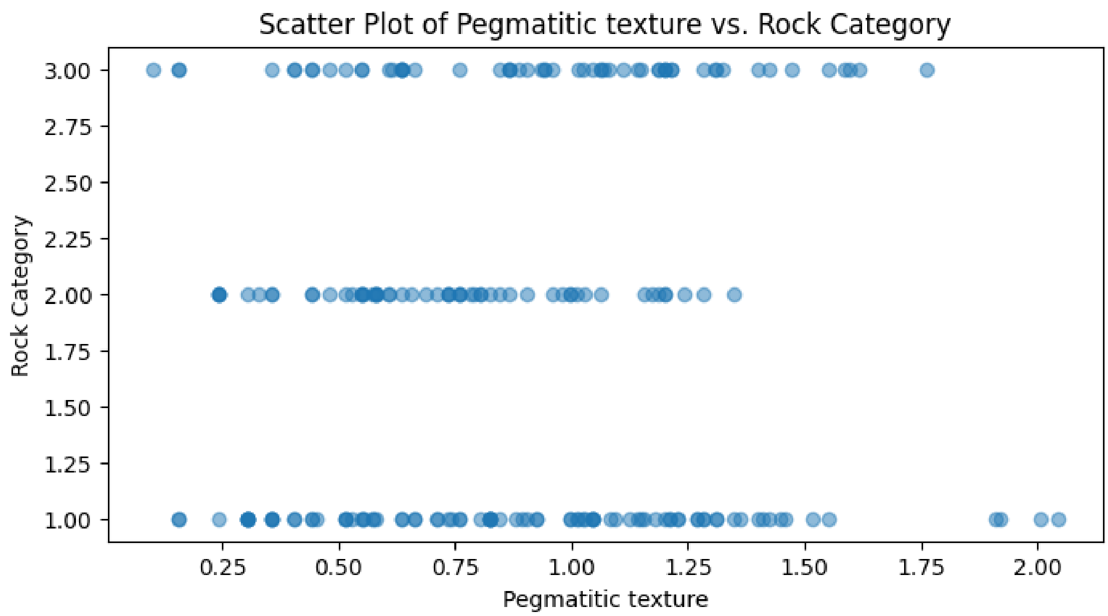
For training data, used token numbers 1-10, for validation 11 to 13, and for testing 14 to 16 (each of the 30 rock subtypes has 16 token numbers).

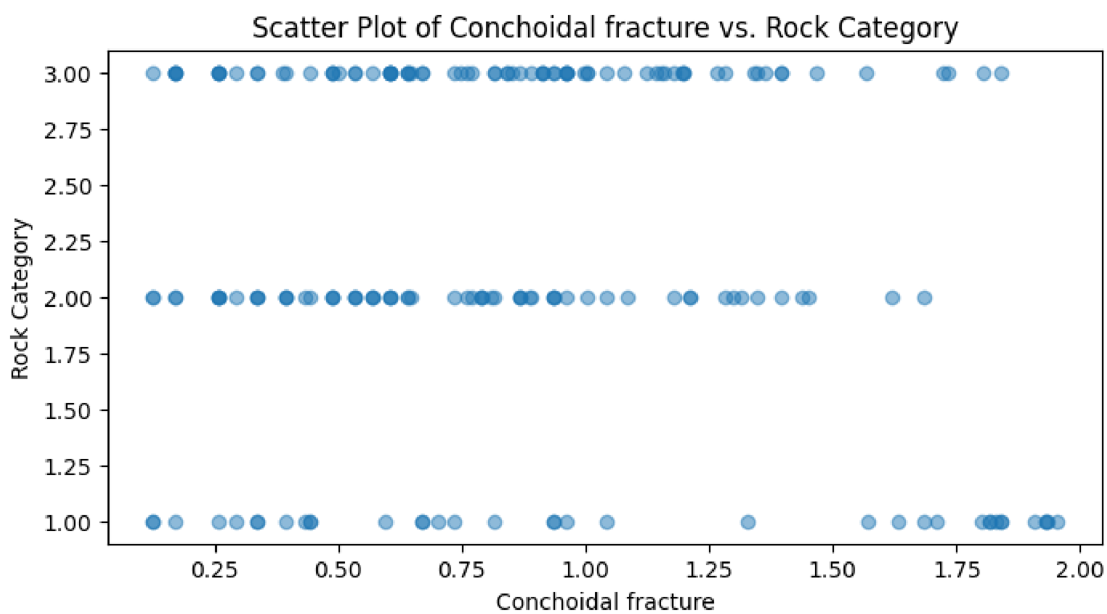
[13]:
```python
# Concatenate the two dataframes
full_data = pd.concat([rock_data, attribute_data,token_data], axis=1)
for column in attribute_data.columns:
    plt.figure(figsize=(8, 4))
    plt.scatter(full_data[column], full_data["rock category"], alpha=0.5)
    plt.title(f'Scatter Plot of {column} vs. Rock Category')
    plt.xlabel(column)
    plt.ylabel("Rock Category")
    plt.show()
```

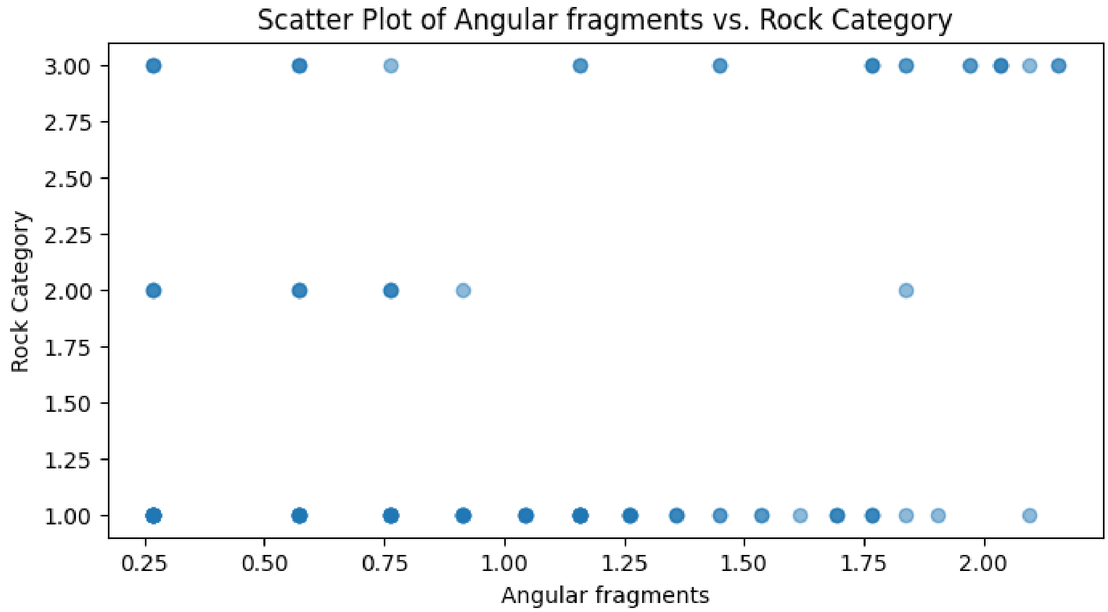


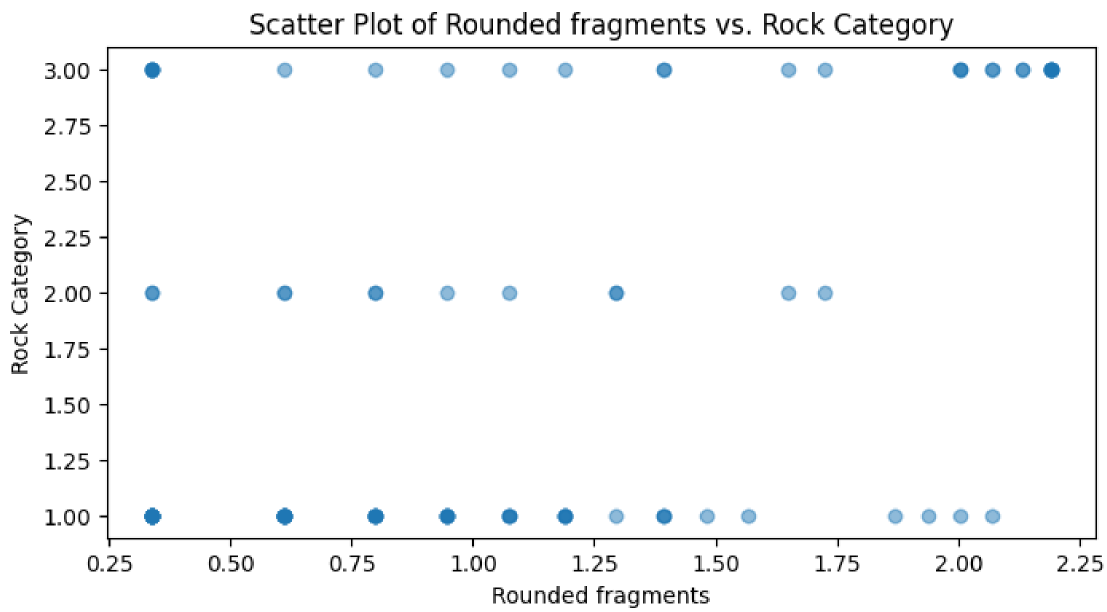

Scatter Plot of Presence of holes vs. Rock Category
Rock Category
Presence of holes
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

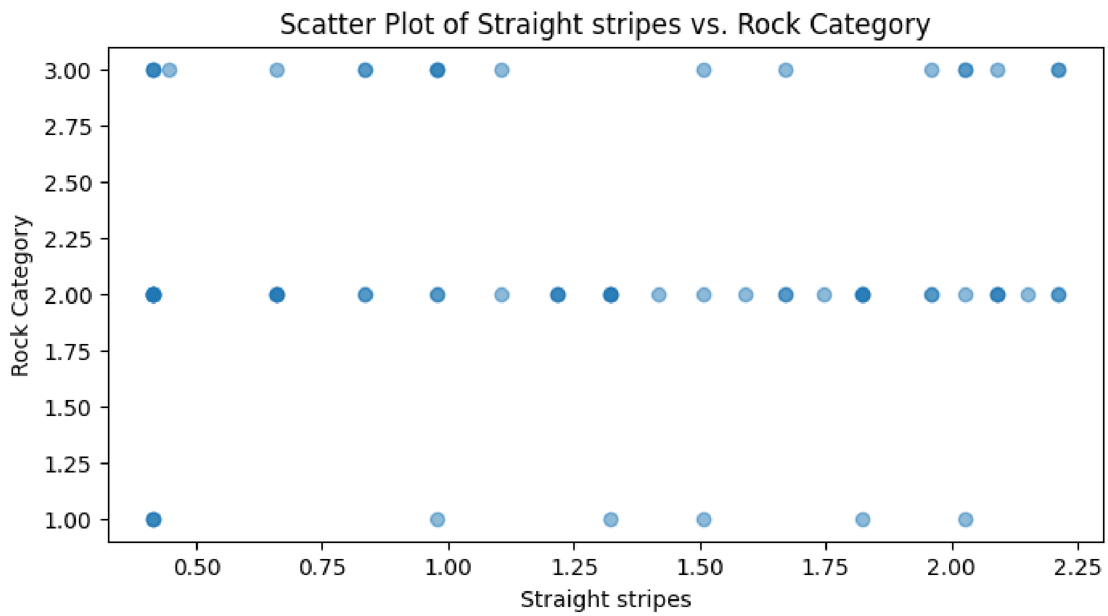

Scatter Plot of Salient green hue vs. Rock Category
Rock Category
Salient green hue
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6


Scatter Plot of Pegmatitic texture vs. Rock Category
Rock Category
Pegmatitic texture
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

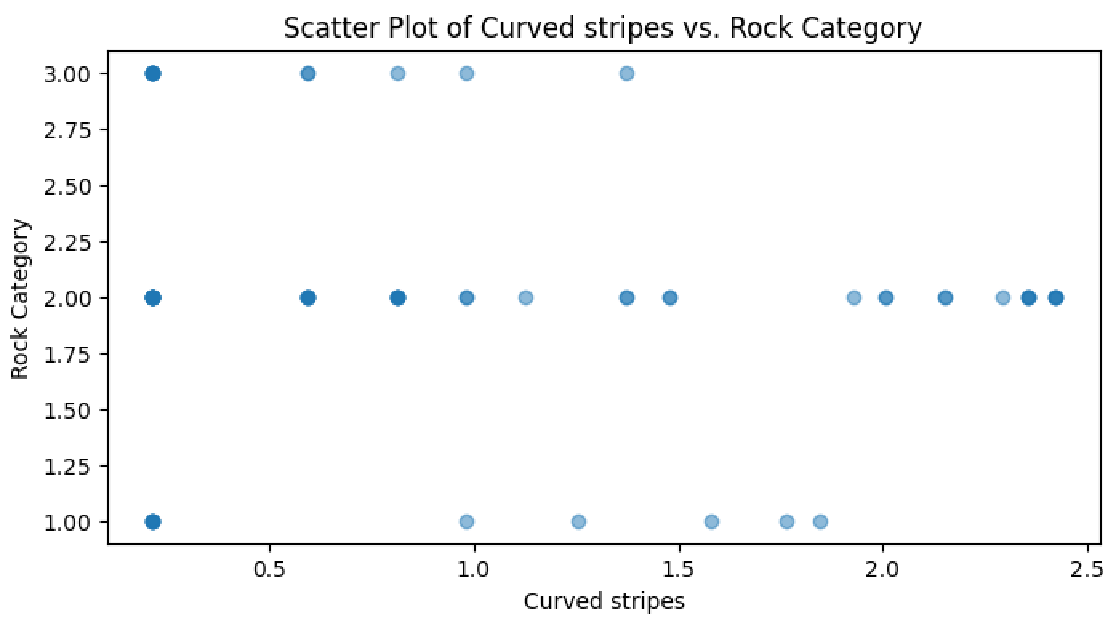

Scatter Plot of Conchoidal fracture vs. Rock Category
Rock Category
Conchoidal fracture
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00


Scatter Plot of Angular fragments vs. Rock Category
Rock Category
Angular fragments
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

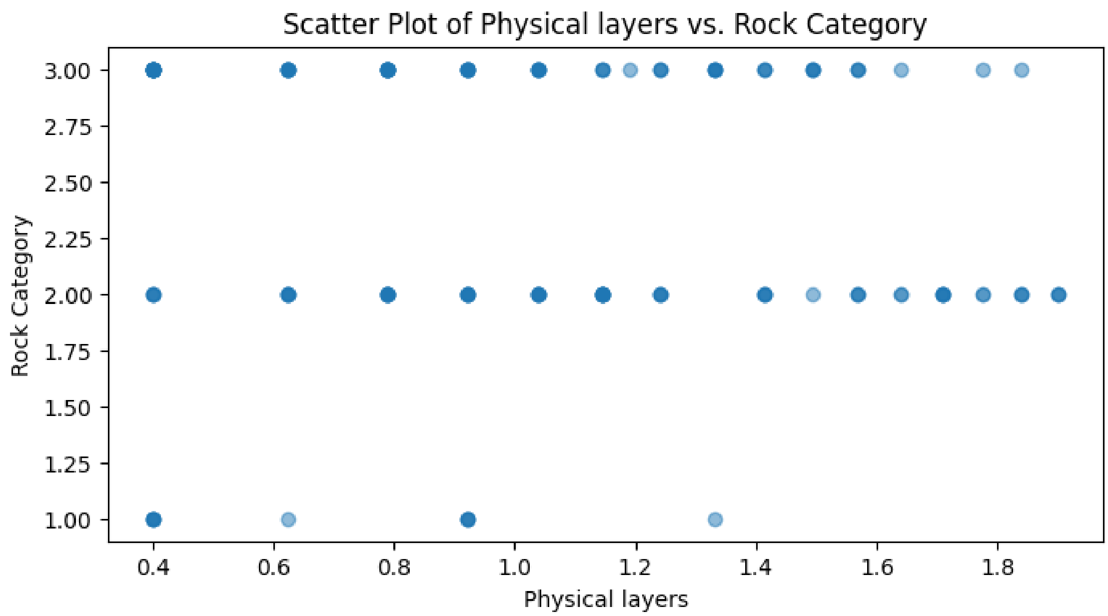

Scatter Plot of Rounded fragments vs. Rock Category
Rock Category
Rounded fragments
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.25

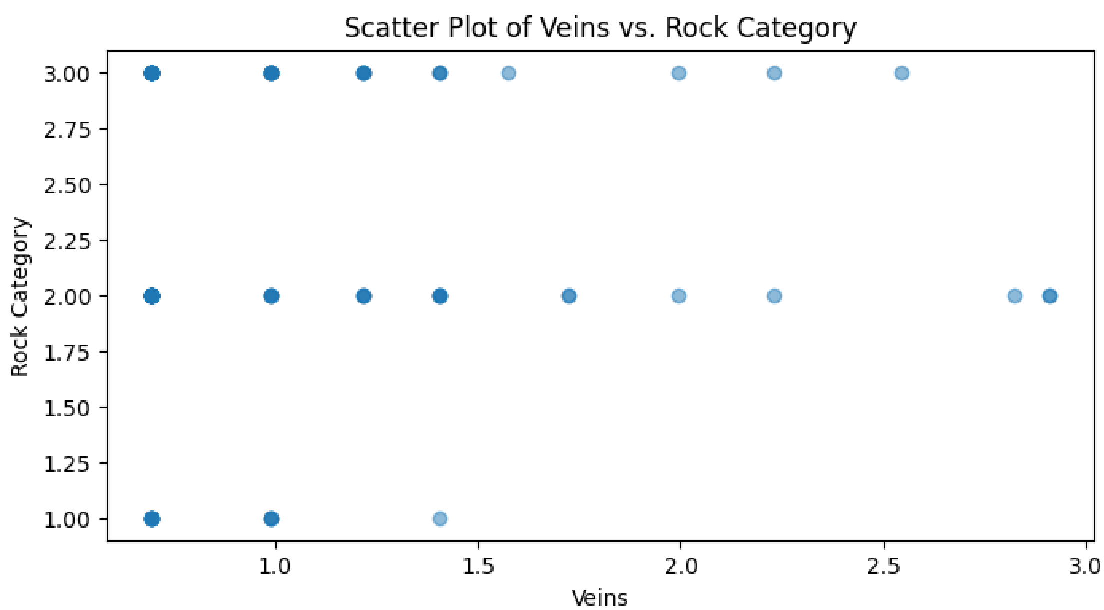


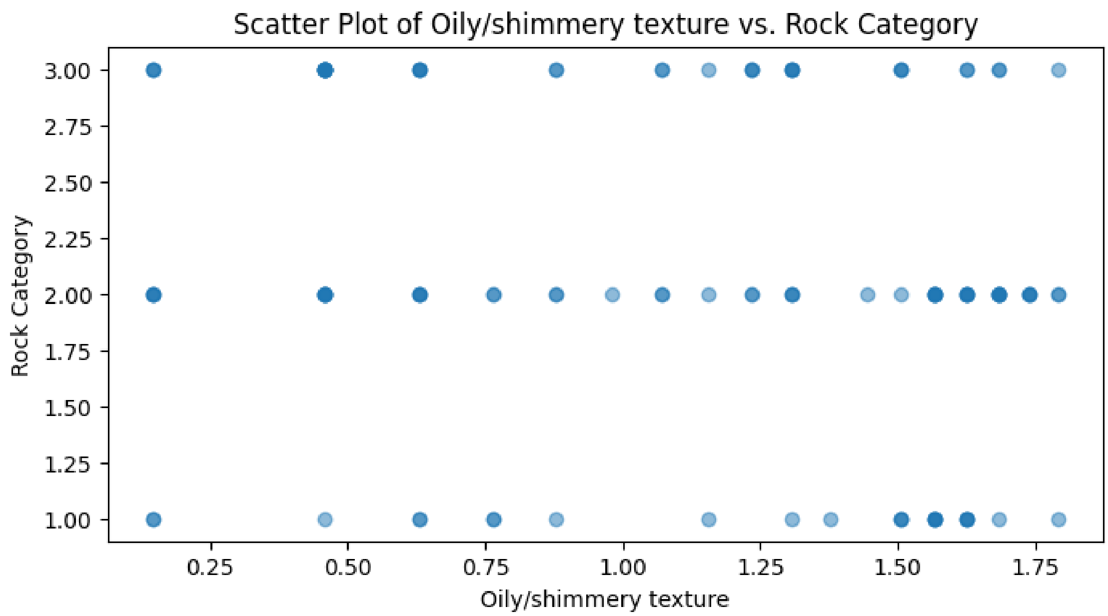
Scatter Plot of Straight stripes vs. Rock Category
Rock Category
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.25
Straight stripes

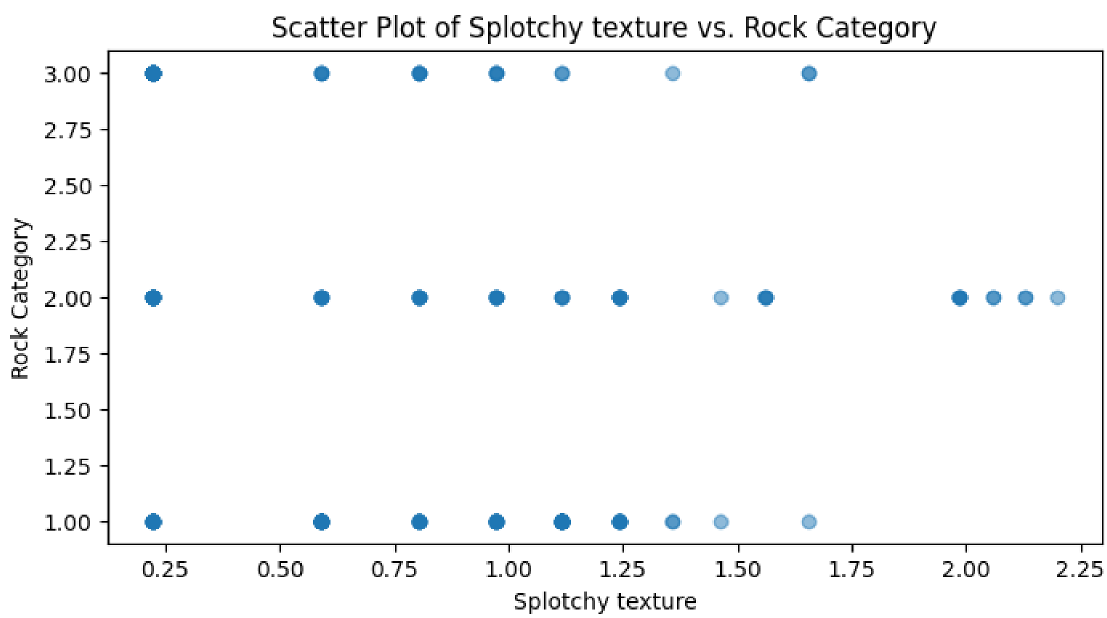


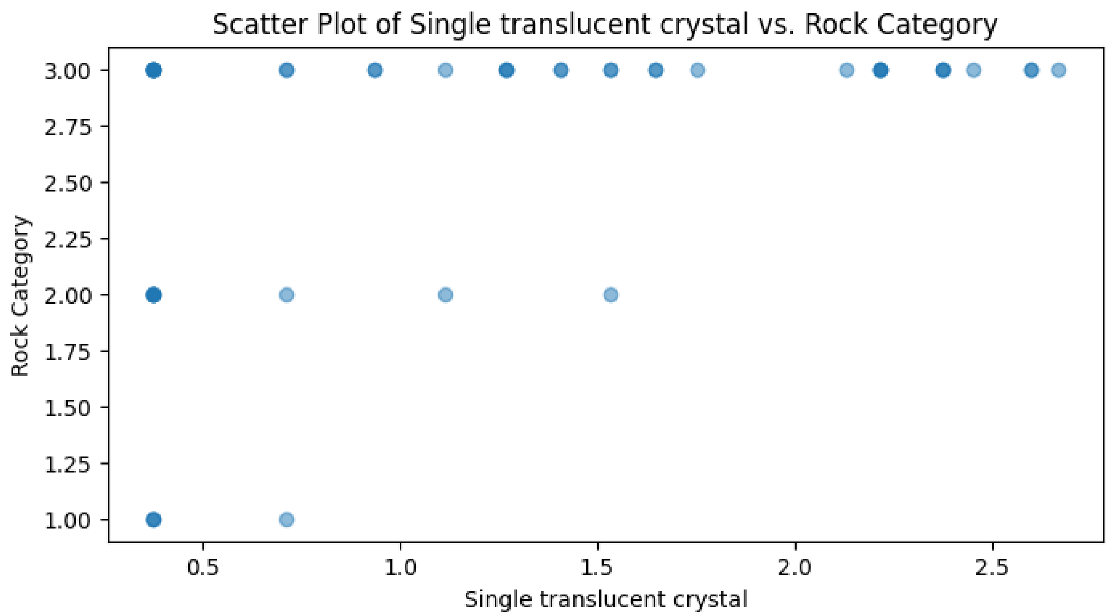
Scatter Plot of Curved stripes vs. Rock Category
Rock Category
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.5
1.0
1.5
2.0
2.5
Curved stripes

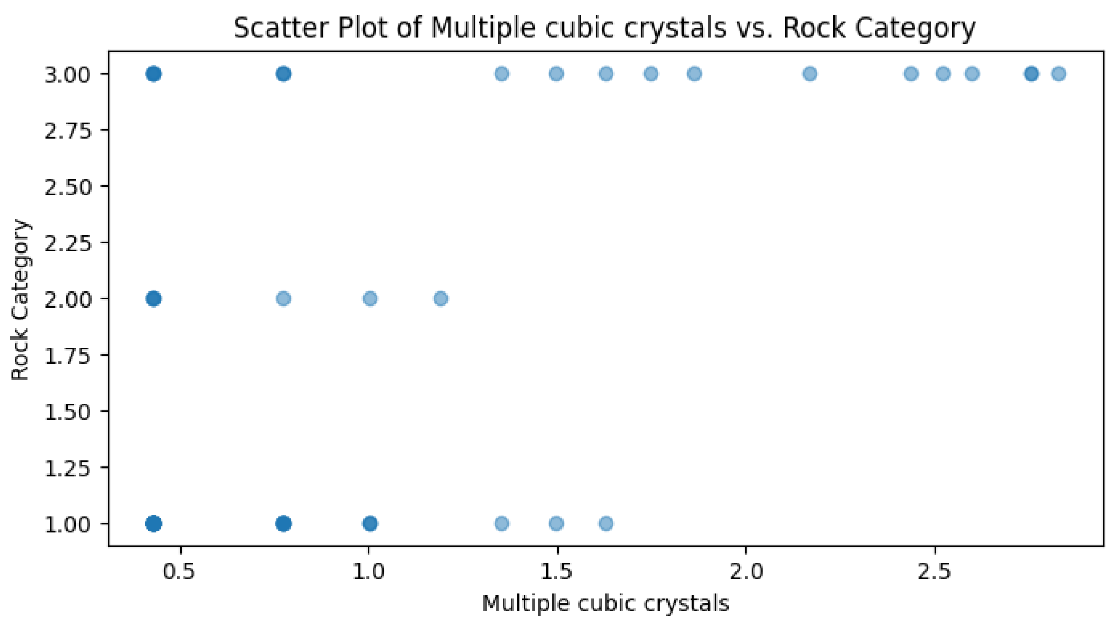

Scatter Plot of Physical layers vs. Rock Category
Rock Category
Physical layers
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1.8

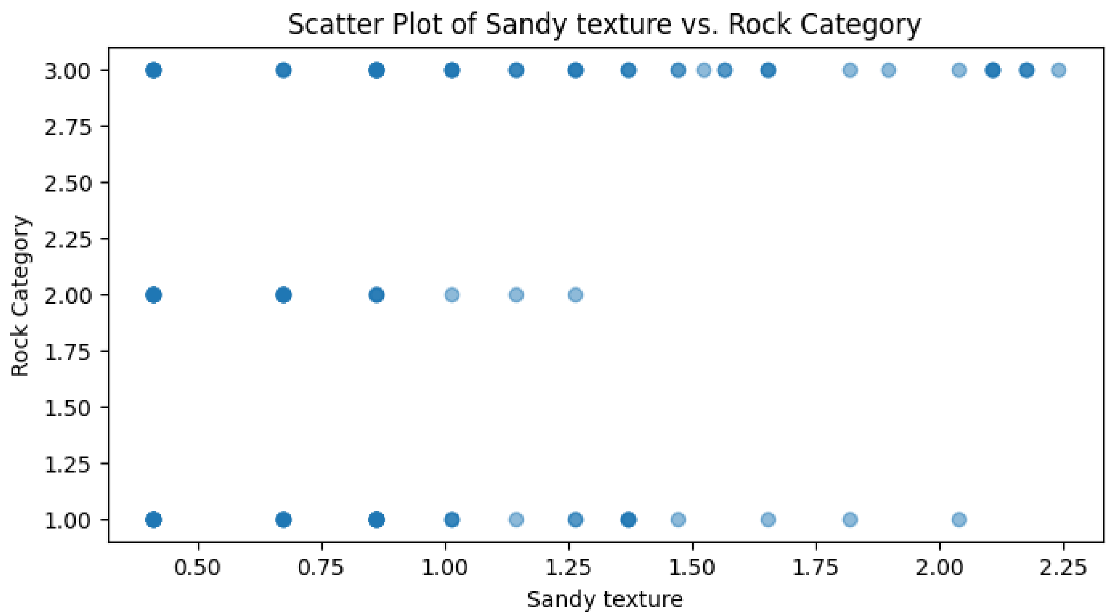

Scatter Plot of Veins vs. Rock Category
Rock Category
Veins
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
1.0
1.5
2.0
2.5
3.0

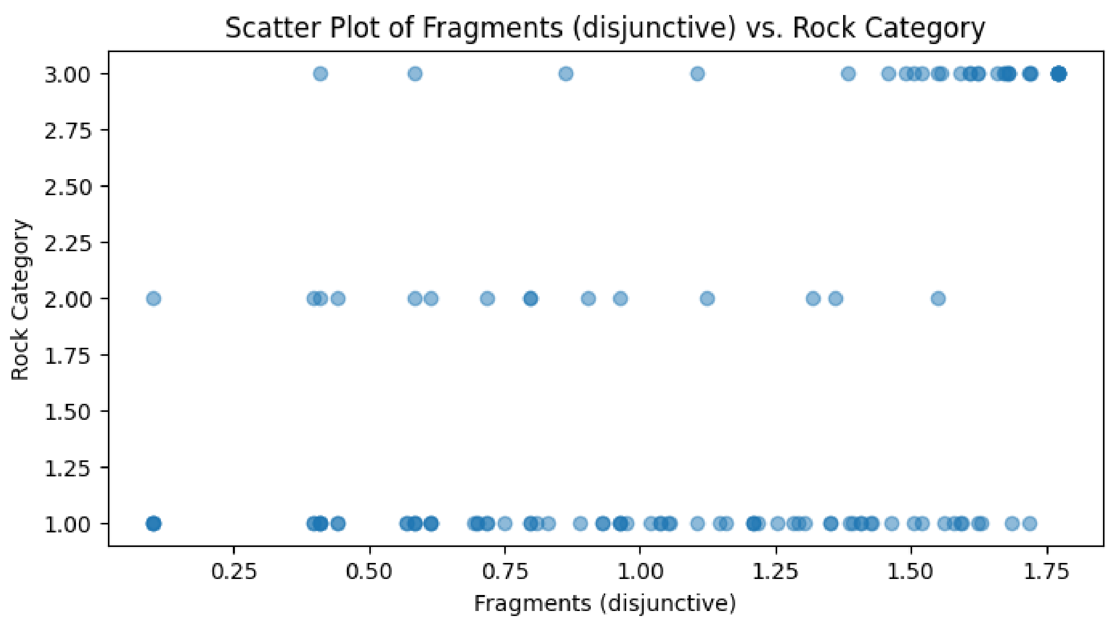

Scatter Plot of Oily/shimmery texture vs. Rock Category
Rock Category
Oily/shimmery texture
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75

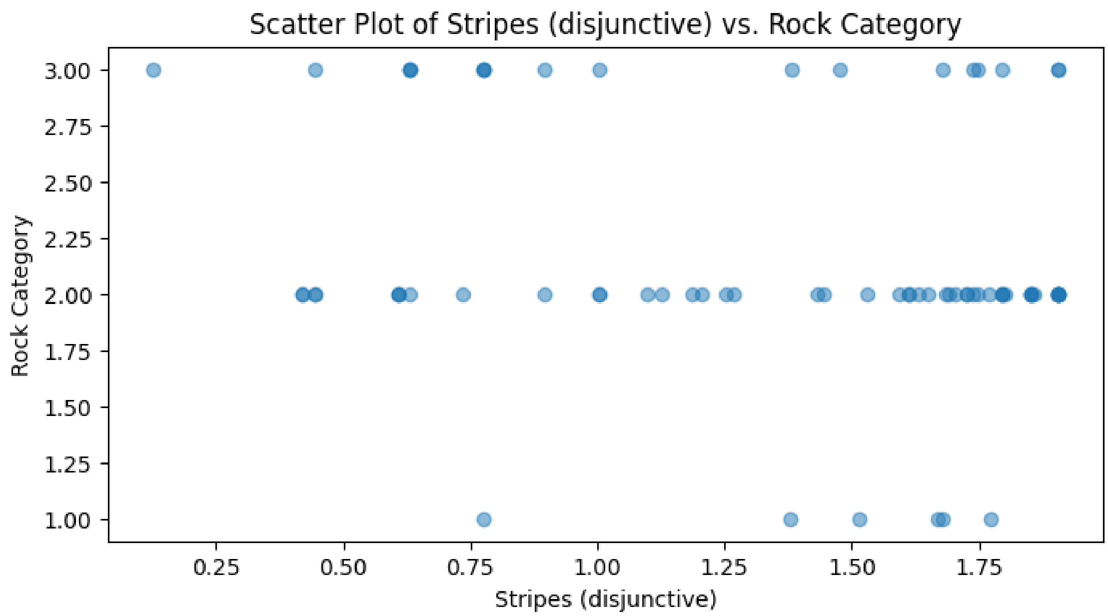

Scatter Plot of Splotchy texture vs. Rock Category
Rock Category
Splotchy texture
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.25

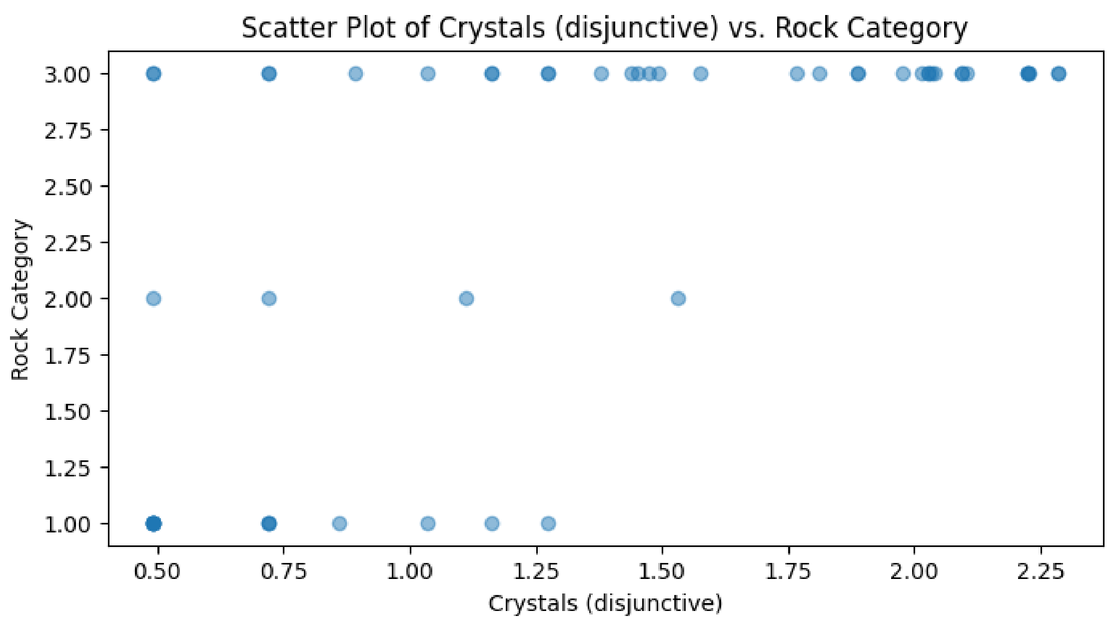

Scatter Plot of Single translucent crystal vs. Rock Category
Rock Category
Single translucent crystal
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.5
1.0
1.5
2.0
2.5


Scatter Plot of Multiple cubic crystals vs. Rock Category
Rock Category
Multiple cubic crystals
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.5
1.0
1.5
2.0
2.5


Scatter Plot of Sandy texture vs. Rock Category
Rock Category
Sandy texture
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.25


Scatter Plot of Fragments (disjunctive) vs. Rock Category
Rock Category
Fragments (disjunctive)
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75





Looking at how the attributes and the label relate to each other:

- Attributes like “Crystals (disjunctive),” “Multiple cubic crystals,” and “Single translucent crystal” seem to go up as the label goes up too. This shows they’ve got a strong connection where if one is big, the other one is likely to be big too.
- For attributes such as “Presence of holes,” “Sandy texture,” and “Fragments (disjunctive),”

they kind of have a good connection with the label as well, but it's not as strong.

- Then there are attributes like "Rounded fragments" and "Angular fragments" that also go up with the label, but the connection is not that big.
- On the flip side, attributes that have a negative link, like "Veins," go in the opposite direction of the label. So if the value for "Veins" is high, the label value tends to be lower.
- There are some attributes, "Porphyritic texture" and "Pegmatitic texture," that don't really move much in line with the label. They don't show much of a link.

Knowing these connections is super helpful because it tells us which attributes can really help us guess the label's values better.

[14]:
```
full_data.describe()
full_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 480 entries, 0 to 479
Data columns (total 21 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   rock category              480 non-null    int64
 1   Porphyritic texture        195 non-null    float64
 2   Presence of holes          93 non-null     float64
 3   Salient green hue          187 non-null    float64
 4   Pegmatitic texture         208 non-null    float64
 5   Conchoidal fracture        180 non-null    float64
 6   Angular fragments          105 non-null    float64
 7   Rounded fragments          98 non-null     float64
 8   Straight stripes           69 non-null     float64
 9   Curved stripes             69 non-null     float64
 10  Physical layers            142 non-null    float64
 11  Veins                      99 non-null     float64
 12  Oily/shimmery texture      113 non-null    float64
 13  Splotchy texture           187 non-null    float64
 14  Single translucent crystal 48 non-null     float64
 15  Multiple cubic crystals    62 non-null     float64
 16  Sandy texture              128 non-null    float64
 17  Fragments (disjunctive)    121 non-null    float64
 18  Stripes (disjunctive)      73 non-null     float64
 19  Crystals (disjunctive)     53 non-null     float64
 20  Token Number               480 non-null    int64
dtypes: float64(19), int64(2)
memory usage: 78.9 KB
```

[15]:
```
# Drop the specified columns from the DataFrame
features_updated=full_data.copy()
```

```python
features_updated.drop(columns=[features_updated.columns[0], features_updated.
  ↪columns[3], features_updated.columns[7], features_updated.columns[9],␣
  ↪features_updated.columns[10]],axis=1)
```

[15]:

```
     Porphyritic texture  Presence of holes  Pegmatitic texture  \
0               1.300180                NaN            0.357662
1               1.290572                NaN                 NaN
2               1.494362                NaN                 NaN
3               1.487684                NaN                 NaN
4               1.352725           0.621102            0.305586
..                   …                  …                  …
475                  NaN                NaN                 NaN
476                  NaN                NaN                 NaN
477                  NaN                NaN                 NaN
478                  NaN                NaN                 NaN
479             1.235386           0.432920                 NaN

     Conchoidal fracture  Angular fragments  Straight stripes     Veins  \
0                    NaN           1.692859               NaN       NaN
1                    NaN           1.616103               NaN       NaN
2                    NaN           0.268257               NaN       NaN
3                    NaN           1.158394               NaN       NaN
4                    NaN           1.263273               NaN       NaN
..                   …                  …               …        …
475                  NaN                NaN               NaN       NaN
476             0.501798                NaN               NaN       NaN
477                  NaN                NaN               NaN  0.696042
478             0.768152                NaN               NaN       NaN
479                  NaN           0.761529               NaN       NaN

     Oily/shimmery texture  Splotchy texture  Single translucent crystal  \
0                      NaN               NaN                         NaN
1                      NaN          1.115985                         NaN
2                      NaN               NaN                         NaN
3                      NaN               NaN                         NaN
4                      NaN          0.804748                         NaN
..                     …               …                         …
475                    NaN               NaN                         NaN
476                    NaN               NaN                         NaN
477                    NaN               NaN                         NaN
478                    NaN               NaN                         NaN
479                    NaN          1.115985                         NaN

     Multiple cubic crystals  Sandy texture  Fragments (disjunctive)  \
0                   0.430709            NaN                 1.429314
1                        NaN            NaN                 1.290684
2                        NaN            NaN                 1.625034
```

```
3                   NaN          NaN                1.630684
4                   NaN          NaN                1.217344
..                  …          …                   …
475                 NaN     1.143569                     NaN
476                 NaN     0.673284                     NaN
477                 NaN     0.673284                     NaN
478                 NaN     0.410488                     NaN
479                 NaN          NaN                0.584390

     Stripes (disjunctive)  Crystals (disjunctive)  Token Number
0                      NaN                     NaN             1
1                      NaN                     NaN             2
2                      NaN                     NaN             3
3                      NaN                     NaN             4
4                      NaN                     NaN             5
..                     …                     …           …
475                    NaN                     NaN            12
476                    NaN                     NaN            13
477                    NaN                     NaN            14
478                    NaN                     NaN            15
479                    NaN                     NaN            16

[480 rows x 16 columns]
```

[16]:
```python
features_updated.head()
```

[16]:
```
   rock category  Porphyritic texture  Presence of holes  Salient green hue  \
0              1             1.300180                NaN                NaN
1              1             1.290572                NaN           0.926814
2              1             1.494362                NaN                NaN
3              1             1.487684                NaN           1.062968
4              1             1.352725           0.621102                NaN

   Pegmatitic texture  Conchoidal fracture  Angular fragments  \
0            0.357662                  NaN           1.692859
1                 NaN                  NaN           1.616103
2                 NaN                  NaN           0.268257
3                 NaN                  NaN           1.158394
4            0.305586                  NaN           1.263273

   Rounded fragments  Straight stripes  Curved stripes  …  Veins  \
0           0.612628               NaN             NaN  …    NaN
1                NaN               NaN             NaN  …    NaN
2           2.004403               NaN             NaN  …    NaN
3           1.938419               NaN             NaN  …    NaN
4           0.946385               NaN             NaN  …    NaN
```

```
   Oily/shimmery texture  Splotchy texture  Single translucent crystal  \
0                    NaN               NaN                         NaN
1                    NaN          1.115985                         NaN
2                    NaN               NaN                         NaN
3                    NaN               NaN                         NaN
4                    NaN          0.804748                         NaN

   Multiple cubic crystals  Sandy texture  Fragments (disjunctive)  \
0                 0.430709            NaN                 1.429314
1                      NaN            NaN                 1.290684
2                      NaN            NaN                 1.625034
3                      NaN            NaN                 1.630684
4                      NaN            NaN                 1.217344

   Stripes (disjunctive)  Crystals (disjunctive)  Token Number
0                    NaN                     NaN             1
1                    NaN                     NaN             2
2                    NaN                     NaN             3
3                    NaN                     NaN             4
4                    NaN                     NaN             5

[5 rows x 21 columns]
```

[17]:
```
# Calculate the median for each column in your DataFrame
med=full_data.median()
medians = features_updated.median()

# Replace null values with the respective column's median
data_filled=full_data.fillna(med)
features_updated = features_updated.fillna(medians)

# Now, features_filled contains no null values, and missing values have been␣
↪replaced with medians.
features_updated.isnull().any()
```

[17]:
```
rock category              False
Porphyritic texture        False
Presence of holes          False
Salient green hue          False
Pegmatitic texture         False
Conchoidal fracture        False
Angular fragments          False
Rounded fragments          False
Straight stripes           False
Curved stripes             False
Physical layers            False
Veins                      False
```

```
Oily/shimmery texture        False
Splotchy texture             False
Single translucent crystal   False
Multiple cubic crystals      False
Sandy texture                False
Fragments (disjunctive)      False
Stripes (disjunctive)        False
Crystals (disjunctive)       False
Token Number                 False
dtype: bool
```

[18]:
```
features_updated.describe()
```

[18]:
```
       rock category  Porphyritic texture  Presence of holes  \
count     480.000000           480.000000         480.000000
mean        2.000000             0.984612           0.680183
std         0.817348             0.231117           0.322678
min         1.000000             0.166334           0.297062
25%         1.000000             1.001720           0.621102
50%         2.000000             1.001720           0.621102
75%         3.000000             1.001720           0.621102
max         3.000000             1.556374           2.133324

       Salient green hue  Pegmatitic texture  Conchoidal fracture  \
count         480.000000          480.000000           480.000000
mean            0.907812            0.847419             0.812290
std             0.275591            0.259320             0.297856
min             0.078070            0.102421             0.125140
25%             0.904902            0.835290             0.788649
50%             0.904902            0.835290             0.788649
75%             0.904902            0.835290             0.788649
max             1.658430            2.043500             1.952706

       Angular fragments  Rounded fragments  Straight stripes  Curved stripes  \
count         480.000000         480.000000        480.000000      480.000000
mean            1.045412           0.968661          1.313165        0.832654
std             0.267116           0.281885          0.236551        0.303340
min             0.268257           0.339333          0.414425        0.214294
25%             1.043021           0.946385          1.320663        0.811304
50%             1.043021           0.946385          1.320663        0.811304
75%             1.043021           0.946385          1.320663        0.811304
max             2.154913           2.190463          2.211099        2.421300

       …       Veins  Oily/shimmery texture  Splotchy texture  \
count  …  480.000000             480.000000        480.000000
mean   …    0.765615               1.204230          0.820607
std    …    0.269947               0.261883          0.307578
```

```
min    ...    0.696042              0.146615         0.223197
25%    ...    0.696042              1.233110         0.804748
50%    ...    0.696042              1.233110         0.804748
75%    ...    0.696042              1.233110         0.804748
max    ...    2.908188              1.790812         2.198235

       Single translucent crystal  Multiple cubic crystals  Sandy texture  \
count                  480.000000               480.000000     480.000000
mean                     1.123712                 0.793173       0.889257
std                      0.254552                 0.259142       0.266882
min                      0.373464                 0.430709       0.410488
25%                      1.114300                 0.772053       0.859142
50%                      1.114300                 0.772053       0.859142
75%                      1.114300                 0.772053       0.859142
max                      2.668335                 2.825964       2.238372

       Fragments (disjunctive)  Stripes (disjunctive)  Crystals (disjunctive)  \
count               480.000000             480.000000              480.000000
mean                  1.147287               1.555810                1.281716
std                   0.246162               0.219072                0.209589
min                   0.102093               0.126127                0.492242
25%                   1.159299               1.593487                1.274403
50%                   1.159299               1.593487                1.274403
75%                   1.159299               1.593487                1.274403
max                   1.771262               1.905183                2.284030

       Token Number
count    480.000000
mean       8.500000
std        4.614582
min        1.000000
25%        4.750000
50%        8.500000
75%       12.250000
max       16.000000

[8 rows x 21 columns]
```

[19]:
```
rock_data.describe()
```

[19]:
```
       rock category
count     480.000000
mean        2.000000
std         0.817348
min         1.000000
25%         1.000000
50%         2.000000
```

```
75%          3.000000
max          3.000000
```

[20]:
```
train_data = features_updated[features_updated['Token Number'].between(1,10)]
validation_data = features_updated[features_updated['Token Number'].
 ↪between(11,13)]
test_data = features_updated[features_updated['Token Number'].between(14,16)]
```

Training different classifiers and tweak the hyperparameters to improve performance (used the grid search if you want or manually try different values). Reporting training, validation and testing performance (classification accuracy, precision, recall and F1 score) and discuss the impact of the hyperparameters

Multinomial Logistic Regression (softmax regression); hyperparameters to explore: C, solver, max number of iterations.

Support vector machines (make sure to try using kernels); hyperparameters to explore: C, kernel, degree of polynomial kernel, gamma.

Random Forest classifier (also analyze feature importance); hyperparameters to explore: the number of trees, max depth, the minimum number of samples required to split an internal node, the minimum number of samples required to be at a leaf node.

Softmax regression

[21]:
```
x_train = train_data.iloc[:, 1:]
y_train = train_data.iloc[:, 0]

x_valid = validation_data.iloc[:, 1:]
y_valid = validation_data.iloc[:,0]

x_test = test_data.iloc[:, 1:]
y_test = test_data.iloc[:,0]
```

[28]:
```
from sklearn.linear_model import LogisticRegression as lg
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score
from sklearn.model_selection import GridSearchCV
import warnings

warnings.filterwarnings('ignore')

# ... (your data preparation and feature extraction code)

# Hyperparameter grid
param_grid = {'C': [0.001, 0.01, 0.1, 1, 10, 100],
              'solver': ['newton-cg', 'lbfgs', 'liblinear'],
              'max_iter': [100, 200, 300, 400, 500]}
```

```
sfmax_reg = lg(multi_class="multinomial", solver="lbfgs", C=10)

grid = GridSearchCV(sfmax_reg, param_grid, cv=3, scoring='accuracy')
grid.fit(x_train, y_train)

best_params = grid.best_params_

best_sf_train = lg(multi_class="multinomial", **best_params)
best_sf_train.fit(x_train, y_train)

# Make predictions on the training, validation, and test sets
train_predictions = best_sf_train.predict(x_train)
val_predictions = best_sf_train.predict(x_valid)
test_predictions = best_sf_train.predict(x_test)

# Calculate accuracy for training, validation, and test sets
train_accuracy = accuracy_score(y_train, train_predictions)
val_accuracy = accuracy_score(y_valid, val_predictions)
test_accuracy = accuracy_score(y_test, test_predictions)

# Calculate F1 scores, precision, and recall for training set
precision_train = precision_score(y_train, train_predictions,␣
 ↪average='weighted')
recall_train = recall_score(y_train, train_predictions, average='weighted')
f1_train = f1_score(y_train, train_predictions, average='weighted')

# Calculate F1 scores, precision, and recall for validation set
precision_val = precision_score(y_valid, val_predictions, average='weighted')
recall_val = recall_score(y_valid, val_predictions, average='weighted')
f1_val = f1_score(y_valid, val_predictions, average='weighted')

# Calculate F1 scores, precision, and recall for test set
precision_test = precision_score(y_test, test_predictions, average='weighted')
recall_test = recall_score(y_test, test_predictions, average='weighted')
f1_test = f1_score(y_test, test_predictions, average='weighted')

# Print results for Logistic Regression model
print("Logistic Regression Model Results:")
print("\nTraining Set:")
print(f"Accuracy: {train_accuracy}")
print(f"Precision: {precision_train}")
print(f"Recall: {recall_train}")
print(f"F1 Score: {f1_train}")

print("\nValidation Set:")
print(f"Accuracy: {val_accuracy}")
print(f"Precision: {precision_val}")
```

```
print(f"Recall: {recall_val}")
print(f"F1 Score: {f1_val}")

print("\nTest Set:")
print(f"Accuracy: {test_accuracy}")
print(f"Precision: {precision_test}")
print(f"Recall: {recall_test}")
print(f"F1 Score: {f1_test}")

print(f"\nBest parameters: {best_params}")
```

```
Logistic Regression Model Results:

Training Set:
Accuracy: 0.6066666666666667
Precision: 0.6100264593912507
Recall: 0.6066666666666667
F1 Score: 0.6064709741587809

Validation Set:
Accuracy: 0.5777777777777777
Precision: 0.600409232762174
Recall: 0.5777777777777777
F1 Score: 0.5710871817572358

Test Set:
Accuracy: 0.5888888888888889
Precision: 0.6100486573047549
Recall: 0.5888888888888889
F1 Score: 0.5776332714483358

Best parameters: {'C': 1, 'max_iter': 100, 'solver': 'newton-cg'}
```

Observation:

1) C (Regularization parameter): The grid search explored different values of C ranging from 0.001 to 100. The best-performing C value was determined to be 10. This suggests that a moderate level of regularization is beneficial for the model's performance.

2) Solver: The grid search considered three solvers: 'newton-cg', 'lbfgs', and 'liblinear'. The best solver, based on the cross-validated accuracy, is 'newton-cg'. This indicates that the Newton-Conjugate Gradient solver performed well for your multiclass softmax regression.

3) Max_iter (Maximum number of iterations):The maximum number of iterations (max_iter) considered during the grid search ranged from 100 to 500. The best-performing max_iter value was determined to be 100. This implies that the optimization algorithm converged within the first 100 iterations for the best model.

In summary, the optimal hyperparameters suggest that a moderate level of regularization (C=10), combined with the 'newton-cg' solver and a relatively low number of iterations (max_iter=100), contributes to achieving the best performance for your softmax regression model. These hyperparameter choices aim to balance the model's complexity, convergence efficiency, and regularization strength.

SVM

[26]:
```python
from sklearn.svm import SVC

param_grid_svm = {'C': [0.001, 0.01, 0.1, 1, 10, 100],
                  'kernel': ['linear', 'rbf', 'poly'],
                  'degree': [2, 3, 4],
                  'gamma': ['scale', 'auto']}

svm_model = SVC()

grid_search_svm = GridSearchCV(svm_model, param_grid_svm, cv=3,␣
 ↪scoring='accuracy')
grid_search_svm.fit(x_train, y_train)

best_params_svm = grid_search_svm.best_params_

best_svm = SVC(**best_params_svm)
best_svm.fit(x_train, y_train)

train_predictions_svm = best_svm.predict(x_train)
val_predictions_svm = best_svm.predict(x_valid)
test_predictions_svm = best_svm.predict(x_test)

# Calculate accuracy for SVM model
train_accuracy_svm = accuracy_score(y_train, train_predictions_svm)
val_accuracy_svm = accuracy_score(y_valid, val_predictions_svm)
test_accuracy_svm = accuracy_score(y_test, test_predictions_svm)

# Calculate F1 scores, precision, and recall for SVM model on training set
precision_train_svm = precision_score(y_train, train_predictions_svm,␣
 ↪average='weighted')
recall_train_svm = recall_score(y_train, train_predictions_svm,␣
 ↪average='weighted')
f1_train_svm = f1_score(y_train, train_predictions_svm, average='weighted')

# Calculate F1 scores, precision, and recall for SVM model on validation set
precision_val_svm = precision_score(y_valid, val_predictions_svm,␣
 ↪average='weighted')
recall_val_svm = recall_score(y_valid, val_predictions_svm, average='weighted')
f1_val_svm = f1_score(y_valid, val_predictions_svm, average='weighted')

# Calculate F1 scores, precision, and recall for SVM model on test set
```

```python
precision_test_svm = precision_score(y_test, test_predictions_svm,␣
  ↪average='weighted')
recall_test_svm = recall_score(y_test, test_predictions_svm, average='weighted')
f1_test_svm = f1_score(y_test, test_predictions_svm, average='weighted')

# Print results for SVM model
print("SVM Model Results:")
print("\nTraining Set:")
print(f"Accuracy: {train_accuracy_svm}")
print(f"Precision: {precision_train_svm}")
print(f"Recall: {recall_train_svm}")
print(f"F1 Score: {f1_train_svm}")

print("\nValidation Set:")
print(f"Accuracy: {val_accuracy_svm}")
print(f"Precision: {precision_val_svm}")
print(f"Recall: {recall_val_svm}")
print(f"F1 Score: {f1_val_svm}")

print("\nTest Set:")
print(f"Accuracy: {test_accuracy_svm}")
print(f"Precision: {precision_test_svm}")
print(f"Recall: {recall_test_svm}")
print(f"F1 Score: {f1_test_svm}")

print("\nBest Hyperparameters:")
print(best_params_svm)
```

```
SVM Model Results:

Training Set:
Accuracy: 0.65
Precision: 0.6534839924670434
Recall: 0.65
F1 Score: 0.6485658338470465

Validation Set:
Accuracy: 0.6
Precision: 0.6024024024024024
Recall: 0.6
F1 Score: 0.5918092079286108

Test Set:
Accuracy: 0.6111111111111112
Precision: 0.6179160021265285
Recall: 0.6111111111111112
F1 Score: 0.6066867772750126
```

```
Best Hyperparameters:
{'C': 10, 'degree': 2, 'gamma': 'scale', 'kernel': 'linear'}
```

Observations:

1) C (Regularization parameter): The best value for C is found to be 10. This suggests that the model benefits from a relatively higher value of C, indicating a preference for accurate classification of training points.

2) Kernel: The best-performing kernel is 'linear'. This implies that a linear decision boundary is well-suited for your dataset, and the model may not require the complexity introduced by non-linear kernels like 'rbf' or 'poly'.

3) Degree (Degree of the polynomial kernel function): The best degree for the polynomial kernel is 2. This suggests that a quadratic (second-degree) polynomial is appropriate for capturing the relationships in your data, providing a balance between complexity and overfitting.

4) Gamma: The best value for gamma is 'scale', indicating that the model automatically calculates gamma based on the inverse of the input data's variance. This can adapt to the characteristics of the data.

In summary, the optimal hyperparameters suggest a preference for a linear kernel with higher regularization (C=10) and a quadratic polynomial kernel when non-linearity is required. The choice of 'scale' for gamma indicates adaptability to the data's variance. These observations collectively contribute to achieving a well-performing SVM model on your dataset.

Random forest

[27]:
```
from sklearn.ensemble import RandomForestClassifier

param_grid_rf = {'n_estimators': [50, 100, 150],
                 'max_depth': [None, 10, 20, 30],
                 'min_samples_split': [2, 5, 10],
                 'min_samples_leaf': [1, 2, 4]}

rf_model = RandomForestClassifier()

grid_search_rf = GridSearchCV(rf_model, param_grid_rf, cv=3, scoring='accuracy')
grid_search_rf.fit(x_train, y_train)

best_params_rf = grid_search_rf.best_params_

best_rf = RandomForestClassifier(**best_params_rf)
best_rf.fit(x_train, y_train)

train_predictions_rf = best_rf.predict(x_train)
val_predictions_rf = best_rf.predict(x_valid)
test_predictions_rf = best_rf.predict(x_test)
```

```python
# Calculate accuracy for RandomForest model
train_accuracy_rf = accuracy_score(y_train, train_predictions_rf)
val_accuracy_rf = accuracy_score(y_valid, val_predictions_rf)
test_accuracy_rf = accuracy_score(y_test, test_predictions_rf)

# Calculate F1 scores, precision, and recall for RandomForest model on training␣
↪set
precision_train_rf = precision_score(y_train, train_predictions_rf,␣
↪average='weighted')
recall_train_rf = recall_score(y_train, train_predictions_rf,␣
↪average='weighted')
f1_train_rf = f1_score(y_train, train_predictions_rf, average='weighted')

# Calculate F1 scores, precision, and recall for RandomForest model on␣
↪validation set
precision_val_rf = precision_score(y_valid, val_predictions_rf,␣
↪average='weighted')
recall_val_rf = recall_score(y_valid, val_predictions_rf, average='weighted')
f1_val_rf = f1_score(y_valid, val_predictions_rf, average='weighted')

# Calculate F1 scores, precision, and recall for RandomForest model on test set
precision_test_rf = precision_score(y_test, test_predictions_rf,␣
↪average='weighted')
recall_test_rf = recall_score(y_test, test_predictions_rf, average='weighted')
f1_test_rf = f1_score(y_test, test_predictions_rf, average='weighted')

# Print results for RandomForest model
print("RandomForest Model Results:")
print("\nTraining Set:")
print(f"Accuracy: {train_accuracy_rf}")
print(f"Precision: {precision_train_rf}")
print(f"Recall: {recall_train_rf}")
print(f"F1 Score: {f1_train_rf}")

print("\nValidation Set:")
print(f"Accuracy: {val_accuracy_rf}")
print(f"Precision: {precision_val_rf}")
print(f"Recall: {recall_val_rf}")
print(f"F1 Score: {f1_val_rf}")

print("\nTest Set:")
print(f"Accuracy: {test_accuracy_rf}")
print(f"Precision: {precision_test_rf}")
print(f"Recall: {recall_test_rf}")
print(f"F1 Score: {f1_test_rf}")
```

```python
print("\nBest Hyperparameters:")
print(best_params_rf)
```

```
RandomForest Model Results:

Training Set:
Accuracy: 0.82
Precision: 0.832479302832244
Recall: 0.82
F1 Score: 0.8202455086665613

Validation Set:
Accuracy: 0.7333333333333333
Precision: 0.7362103174603174
Recall: 0.7333333333333333
F1 Score: 0.7342355703868495

Test Set:
Accuracy: 0.6888888888888889
Precision: 0.6879960317460317
Recall: 0.6888888888888889
F1 Score: 0.6879248547769126

Best Hyperparameters:
{'max_depth': 10, 'min_samples_leaf': 2, 'min_samples_split': 5, 'n_estimators':
50}
```

Observation:

1) n_estimators:n: The best value for n_estimators is 50. This parameter defines the number of trees in the forest. A lower value may reduce overfitting and computational cost, and in this case, 50 trees provide good performance
2) . max_dep ion: The best value for max_depth is 30. This parameter controls the maximum depth of each tree in the forest. A higher value allows trees to capture more complex relationships in the data. In this case, a deep tree structure with a maximum depth of 30 is considered opti
3) mal. min_samples_rvation: The best value for min_samples_split is 2. This parameter sets the minimum number of samples required to split an internal node. A lower value allows the model to capture finer patterns in th
4) e data. min_sampservation: The best value for min_samples_leaf is 1. This parameter sets the minimum number of samples required to be at a leaf node. A lower value may lead to more detailed and granular deci

In summary, the best hyperparameters suggest a relatively small number of trees (50), deep trees (max_depth=30) to capture complex relationships, and minimal restrictions on the minimum number of samples for split and leaf nodes. These hyperparameters contribute to achieving a RandomForest model that performs well on your dataset, as indicated by high training accuracy and reasonable generalization to the validation and test sets.sion trees.

Combine your classifiers into an ensemble and try to outperform each individual classifier on the validation set.

Hard Voting

[29]:
```
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import accuracy_score

hard_voting_clf = VotingClassifier(
    estimators=[('lr', best_sf_train), ('svm', best_svm), ('rf', best_rf)],
    voting='hard'
)

hard_voting_clf.fit(x_train, y_train)

train_accuracy_hard = accuracy_score(y_train, hard_voting_clf.predict(x_train))
val_accuracy_hard = accuracy_score(y_valid, hard_voting_clf.predict(x_valid))
test_accuracy_hard = accuracy_score(y_test, hard_voting_clf.predict(x_test))

print("Training Accuracy:", train_accuracy_hard)
print("Validation Accuracy:", val_accuracy_hard)
print("Testing Accuracy:", test_accuracy_hard)
```

```
Training Accuracy: 0.66
Validation Accuracy: 0.6
Testing Accuracy: 0.6111111111111112
```

Soft Voting

[30]:
```
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import accuracy_score

best_svm = SVC(**best_params_svm, probability=True)

soft_voting_clf = VotingClassifier(
    estimators=[('lr', best_sf_train), ('svm', best_svm), ('rf', best_rf)],
    voting='soft'
)

soft_voting_clf.fit(x_train, y_train)

train_accuracy_soft = accuracy_score(y_train, soft_voting_clf.predict(x_train))
val_accuracy_soft = accuracy_score(y_valid, soft_voting_clf.predict(x_valid))
test_accuracy_soft = accuracy_score(y_test, soft_voting_clf.predict(x_test))


print("Training Accuracy:", train_accuracy_soft)
print("Validation Accuracy:", val_accuracy_soft)
print("Test Accuracy:", test_accuracy_soft)
```

```
Training Accuracy: 0.7166666666666667
Validation Accuracy: 0.6888888888888889
Test Accuracy: 0.6444444444444445
```

It appears that assembling the previously trained classifiers into an ensemble using hard voting reduced the score on the validation set compared to our other classifers. The hard voting ensemble gave a validation accuracy of 0.68.

[31]:
```
df = pd.read_csv('/content/trialData.csv')

df_filtered = df[df['rocknumber'].between(1, 480)]

# Separate training (Block 1-3) and test (Block 4) data
train_data = df_filtered[df_filtered['block'].isin([1, 2, 3])]
test_data = df_filtered[df_filtered['block'] == 4]

human_train_accuracy = train_data['cat_correct'].mean()
human_test_accuracy = test_data['cat_correct'].mean()


# Check the calculated values
print("Human train accuracy:",human_train_accuracy)
print("Human test accuracy:",human_test_accuracy)
```

```
Human train accuracy: 0.5599349490660221
Human test accuracy: 0.5984143924378716
```

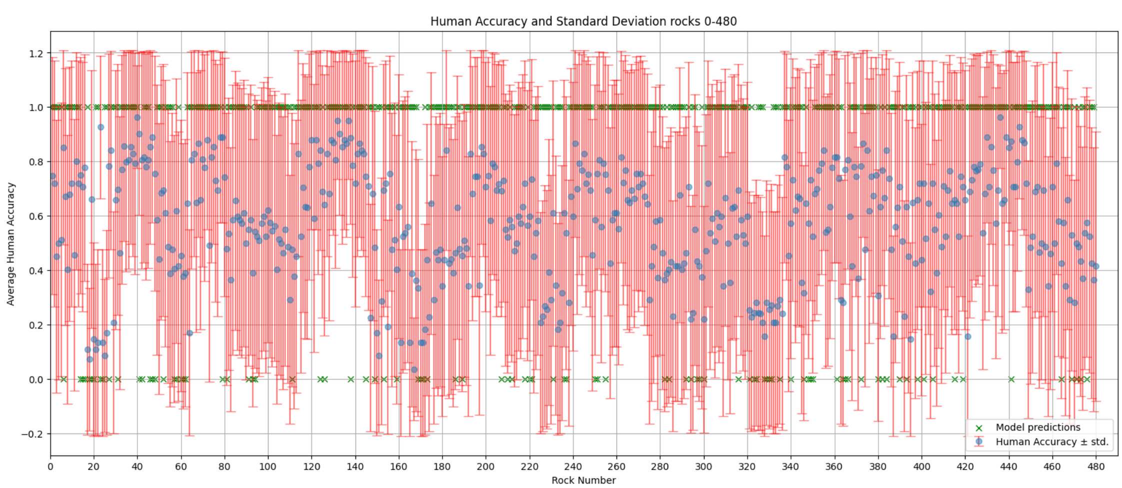
On the train and test set, the humans appear to perform worse than our best model. Our best performing model appears to be the Random Forest model, it has the highest scores on the 3 sets. On the training set, our random forest had an accuracy which was significantly higher than the human. On the test set, our random forest also had an accuracy that is significantly higher than the humans.

When considering our ensemble models, the soft voting model performed the best on the training data with a train accuracy which was higher than the humans train accuracy. The hard voting model performed better on the test set than the humans with a test accuracy that was significantly higher than the humans.

[38]:
```
import pandas as pd
import matplotlib.pyplot as plt

plt.figure(figsize=(20, 8))

#plot human accuracy and std
accuracy_stats = df.groupby('rocknumber')['cat_correct'].agg(['mean', 'std']).
 ↪reset_index()
plt.errorbar(accuracy_stats['rocknumber'], accuracy_stats['mean'],␣
 ↪yerr=accuracy_stats['std'], fmt='o', capsize=5, label='Human Accuracy ± std.
 ↪', alpha=0.5, ecolor = 'r')
```

```
#get testing data for all rocks
testing_data = features_updated[features_updated['Token Number'].between(1,17)]
testing_data_final = testing_data.iloc[:, 1:]

#predict on rocks
predictions = best_rf.predict(testing_data_final)
actual_labels = full_data['rock category']

# Compare predictions to actual labels
correct_predictions = (predictions == actual_labels).astype(int)
predictions_df = pd.DataFrame({'rocknumber': np.arange(0, 480),␣
↪'correct_prediction': predictions})

#add model predictions
plt.scatter(predictions_df['rocknumber'], correct_predictions,  color =␣
↪"green", marker='x', lw=1, label = "Model predictions")

plt.title('Human Accuracy and Standard Deviation rocks 0-480')
plt.xlabel('Rock Number')
plt.ylabel('Average Human Accuracy')

plt.xlim(0, 490)
plt.xticks(range(0, 490, 20))
plt.legend()
plt.grid(True)
plt.show()
```

540
480



Based on the plot of human accuracy and our model's accuracy, we can see that in some spots where the human accuracy was low (blue dots) our model seemed to make the same errors (green x's). If you look at rocks 320-340 you can see that our model was incorrect often where human accuracy is low and the same is also visible around rock 20. This shows that our model is making similar errors as a human but is overall more accurate. This is apparent at multiple points on the plot.

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

[ ]:
```

```