```python
import warnings
warnings.filterwarnings('ignore')

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score,
precision_score, recall_score, f1_score
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import VotingClassifier

aggregrate_rock_data = pd.read_excel(r'C:\Users\charu\Downloads\
aggregateRockData.xlsx',header=None)
category_number_df = aggregrate_rock_data[[1]].rename(columns={1:
'Category number'}).head(480)

feature_presence = pd.read_csv(r'C:\Users\charu\Downloads\
feature_presence540.txt',delim_whitespace=True,header = None)
feature_presence_df = feature_presence.iloc[:480, 2:14]
column_name = ['Token number','Angular fragments','Rounded
fragments','Straight stripes','Curved stripes','Physical
layers','Veins','Oily/shimmery texture',
              'Splotchy texture', 'Single translucent
crystal','Multiple cubic crystals','Sandy texture']
feature_presence_df.columns=column_name
feature_presence_df.head(5)
```

```
  Token number Angular fragments Rounded fragments Straight stripes  \
0            1              0.20              0.15             0.00
1            2              0.65              0.15             0.00
2            3              0.60              0.00             0.00
3            4              0.10              0.85             0.00
4            5              0.35              0.80             0.00

   Curved stripes  Physical layers  Veins  Oily/shimmery texture  \
0             0.0             0.00   0.05                    0.0
1             0.0             0.05   0.00                    0.0
2             0.0             0.05   0.00                    0.0
3             0.0             0.05   0.00                    0.0
4             0.0             0.00   0.00                    0.0

   Splotchy texture  Single translucent crystal  Multiple cubic
crystals  \
0              0.30                         0.0
0.00
```

```
1              0.10                        0.0
0.05
2              0.35                        0.0
0.00
3              0.10                        0.0
0.00
4              0.10                        0.0
0.00

   Sandy texture
0           0.10
1           0.05
2           0.05
3           0.10
4           0.05

#Concats the feature presence and aggregrate rock
rock_df = pd.concat([feature_presence_df, category_number_df], axis=1)
rock_df.head()

rock_df_data = pd.concat([feature_presence_df, category_number_df],
axis=1)
```

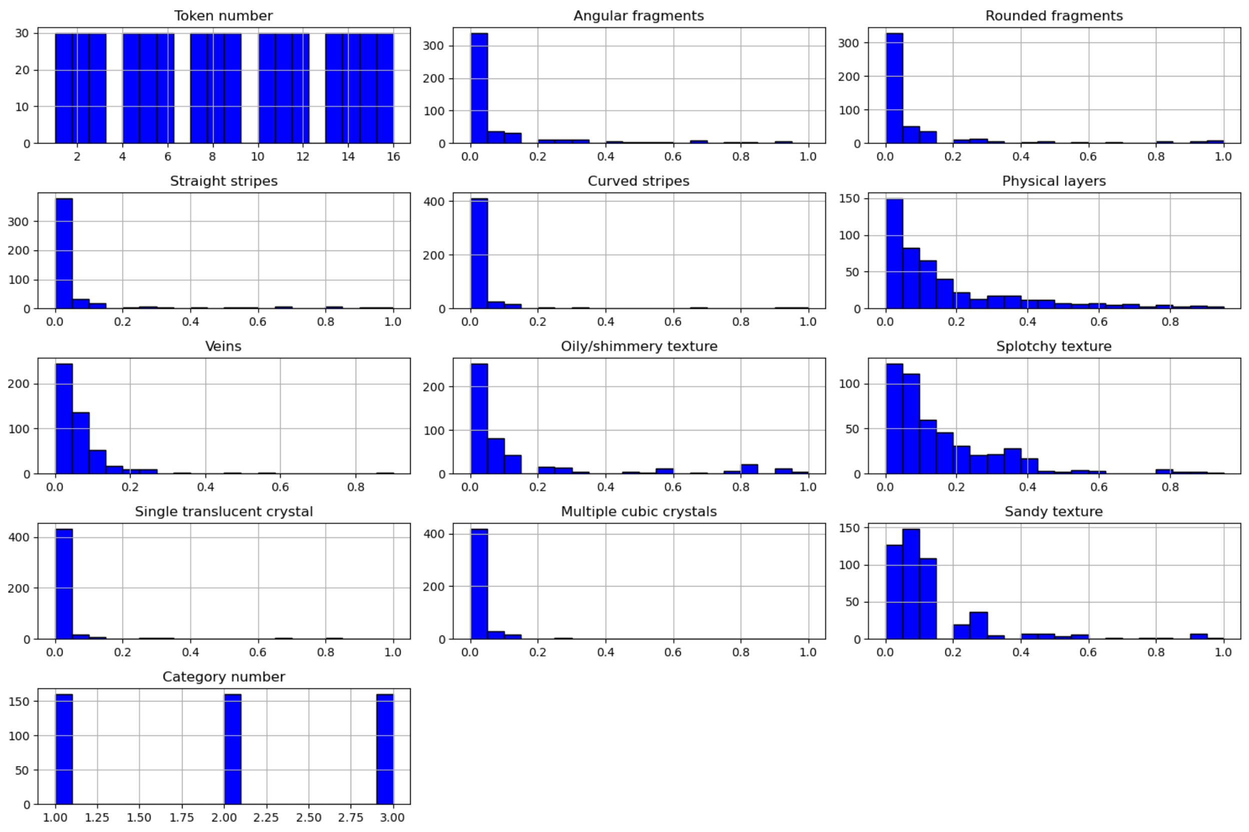
1. Display the statistical values for each of the attributes, along with visualizations (e.g., histogram) of the distributions for each attribute. Are there any attributes that might require special treatment? If so, what special treatment might they require?

```
rock_df.describe()

       Curved stripes  Physical layers       Veins  Oily/shimmery
texture  \
count      480.000000       480.000000  480.000000
480.000000
mean         0.042292         0.165146    0.052396
0.144479
std          0.160970         0.216635    0.102676
0.265689
min          0.000000         0.000000    0.000000
0.000000
25%          0.000000         0.000000    0.000000
0.000000
50%          0.000000         0.100000    0.000000
0.000000
75%          0.000000         0.212500    0.050000
0.100000
max          1.000000         0.950000    0.900000
1.000000

       Splotchy texture  Single translucent crystal  Multiple cubic
crystals  \
count       480.000000                           480.000000
480.000000
mean          0.141458                             0.031667
0.025104
std           0.168222                             0.135647
0.112153
min           0.000000                             0.000000
0.000000
25%           0.000000                             0.000000
0.000000
50%           0.100000                             0.000000
0.000000
75%           0.200000                             0.000000
0.000000
max           0.950000                             1.000000
1.000000

       Sandy texture  Category number
count     480.000000       480.000000
mean        0.119854         2.000000
std         0.173149         0.817348
min         0.000000         1.000000
25%         0.000000         1.000000
50%         0.050000         2.000000
75%         0.150000         3.000000
max         1.000000         3.000000
```

- Curved Stripes: - Has a mean of 0.0423, indicating that most of the values in the curved strips are 0. - It has a maximum value of 1. - Standard Deviation (std): 0.161, indicating a low variance, with most values close to 0.
- Physical Layers: - Has a mean of 0.1651, which was more than the Curved Stripes. - Std: 0.217, showing moderate variation. - Max: 0.95, so the highest value doesn't reach 1, implying physical layers are observed to a significant but not maximal extent.
- Veins: - Mean: 0.0524, indicating veins are rare in most rocks. - Std: 0.103, showing low variability. - Max: 0.9, meaning some rocks have a high concentration of veins, though most values are close to 0.
- Oily/Shimmery Texture: - Mean: 0.1445, indicating this texture is moderately present. - Std: 0.266, suggesting higher variability compared to previous attributes. - Max: 1.0, meaning some rocks have a very high presence of this texture.
- Splotchy Texture: - Mean: 0.1415, with a similar moderate presence to oily texture. - Std: 0.168, showing moderate variance. - Max: 0.95, with some rocks having high values but not maximal.

- Single Translucent Crystal: - Mean: 0.0317, indicating a very low presence. - Std: 0.136, meaning this attribute is mostly close to 0. - Max: 1.0, showing that some rocks have this feature strongly present.
- Multiple Cubic Crystals:
  - Mean: 0.0251, suggesting this attribute is very rare.
  - Std: 0.112, with low variability.
  - Max: 1.0, so some rocks do have multiple cubic crystals prominently.
- Sandy Texture:
  - Mean: 0.1199, moderately present across rocks.
  - Std: 0.173, with a reasonable range of values.
  - Max: 1.0, indicating some rocks have a full sandy texture.
- Category Number:
  - Mean: 2 which indicates that the data is evenly spread across three classes.
  - Std: 0.817, indicating that the categories are relatively balanced.

```python
rock_df = rock_df.apply(pd.to_numeric, errors='coerce')

num_columns = len(rock_df.columns)
num_rows = (num_columns // 3) + 1

# Plot histograms for each numeric attribute
rock_df.hist(bins=20, figsize=(15, 10), layout=(num_rows, 3),
color='blue', edgecolor='black')

# Tight layout to avoid overlap
plt.tight_layout()
plt.show()
```



Right-Skewed Distributions: Curved stripes, Veins, Oily/shimmery texture, Single translucent crystal, and Multiple cubic crystals all exhibit right-skewed distributions. Most of the values are concentrated around 0, with a long tail extending towards the higher values.

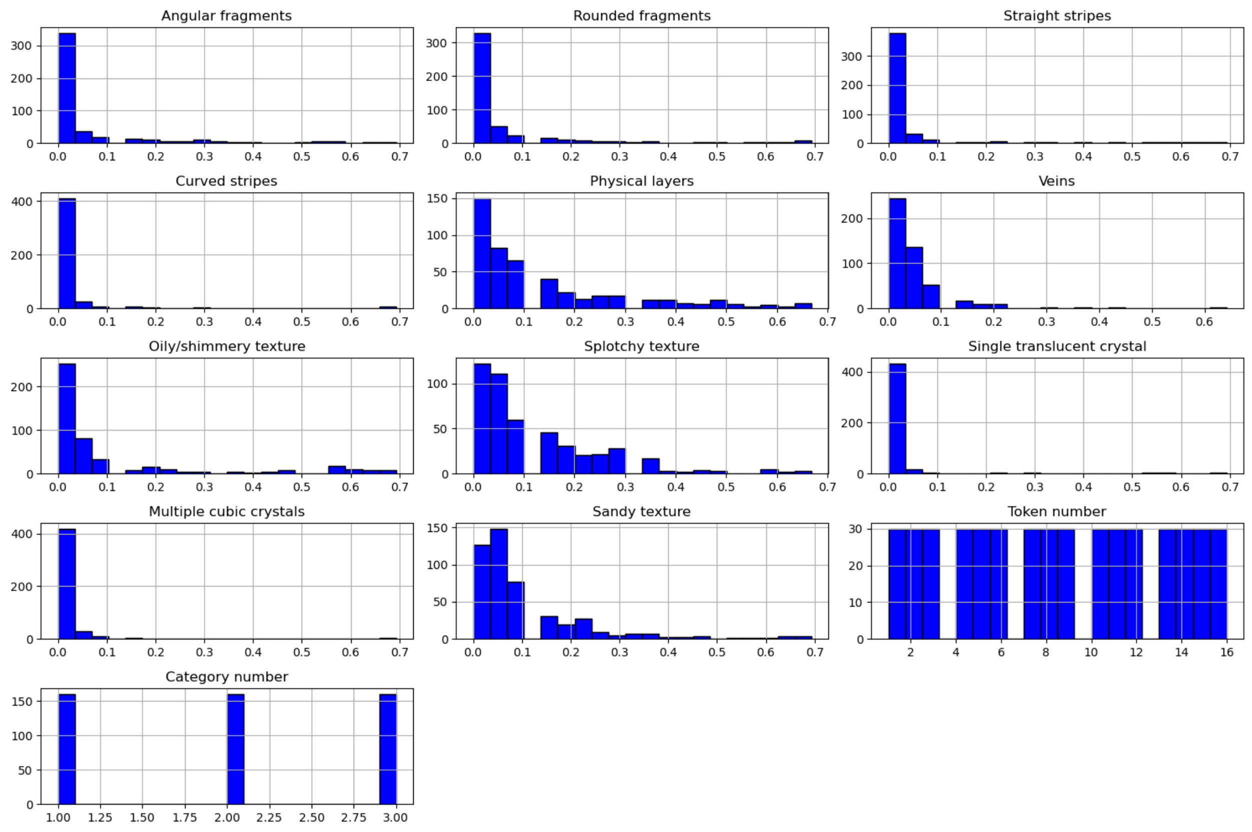
More Evenly Distributed Attributes: Physical layers, Splotchy texture, and Sandy texture show somewhat more gradual distributions compared to the other attributes, but they still exhibit skewness. For example, Splotchy texture and Sandy texture have values spread out between 0 and 0.4, but they are still right-skewed.

Attribuites requiring special treatment: Curved stripes, Veins, Oily/shimmery texture, Single translucent crystal, Multiple cubic crystals, Physical layers, Splotchy texture, and Sandy texture all are skewed towards right which requires special treatment. Logrithmic transformation can be applied to these as this compresses the range of large values, bringing them closer to the smaller ones. For example, in the attribute Veins, where many values are near zero and a few are very large, a log transformation will reduce the impact of those extreme values and balance the distribution.

```
import numpy as np
import pandas as pd

# Check the column names to see the exact names of 'Token number' and
'Category number'
print(rock_df.columns)

# After inspecting the columns, use the correct names in the drop
```

```
method
# For example, if there are spaces or different cases in the column
names, adjust accordingly
columns_to_transform = rock_df.select_dtypes(include=[np.number])

# If 'Token number' and 'Category number' exist, drop them. Otherwise,
drop based on the correct names.
if 'Token number' in columns_to_transform.columns:
    columns_to_transform = columns_to_transform.drop(columns=['Token
number'])

if 'Category number' in columns_to_transform.columns:
    columns_to_transform =
columns_to_transform.drop(columns=['Category number'])

# Apply logarithmic transformation (log1p to handle zero values) to
the selected columns
log_transformed_data = columns_to_transform.apply(lambda x:
np.log1p(x))

# Add back the 'Token number' and 'Category number' columns to the
transformed data (if they exist in the original)
if 'Token number' in rock_df.columns:
    log_transformed_data['Token number'] = rock_df['Token number']

if 'Category number' in rock_df.columns:
    log_transformed_data['Category number'] = rock_df['Category
number']

# Display the transformed data
print(log_transformed_data.head())

# Generate histograms for all numeric columns after logarithmic
transformation
num_columns = len(log_transformed_data.columns)
num_rows = (num_columns // 3) + 1  # Organize layout into rows and
columns for histograms

# Plot histograms for each transformed numeric attribute
log_transformed_data.hist(bins=20, figsize=(15, 10), layout=(num_rows,
3), color='blue', edgecolor='black')

# Tight layout to avoid overlap
plt.tight_layout()
plt.show()
```

```
Index(['Token number', 'Angular fragments', 'Rounded fragments',
       'Straight stripes', 'Curved stripes', 'Physical layers',
'Veins',
       'Oily/shimmery texture', 'Splotchy texture',
       'Single translucent crystal', 'Multiple cubic crystals',
       'Sandy texture', 'Category number'],
      dtype='object')
   Angular fragments  Rounded fragments  Straight stripes  Curved
stripes  \
0           0.182322           0.139762               0.0
0.0
1           0.500775           0.139762               0.0
0.0
2           0.470004           0.000000               0.0
0.0
3           0.095310           0.615186               0.0
0.0
4           0.300105           0.587787               0.0
0.0

   Physical layers    Veins  Oily/shimmery texture  Splotchy
texture  \
0          0.00000  0.04879                    0.0          0.262364

1          0.04879  0.00000                    0.0          0.095310

2          0.04879  0.00000                    0.0          0.300105

3          0.04879  0.00000                    0.0          0.095310

4          0.00000  0.00000                    0.0          0.095310


   Single translucent crystal  Multiple cubic crystals  Sandy texture
\
0                         0.0                  0.00000        0.09531

1                         0.0                  0.04879        0.04879

2                         0.0                  0.00000        0.04879

3                         0.0                  0.00000        0.09531

4                         0.0                  0.00000        0.04879


   Token number  Category number
0             1                1
1             2                1
2             3                1
3             4                1
4             5                1
```

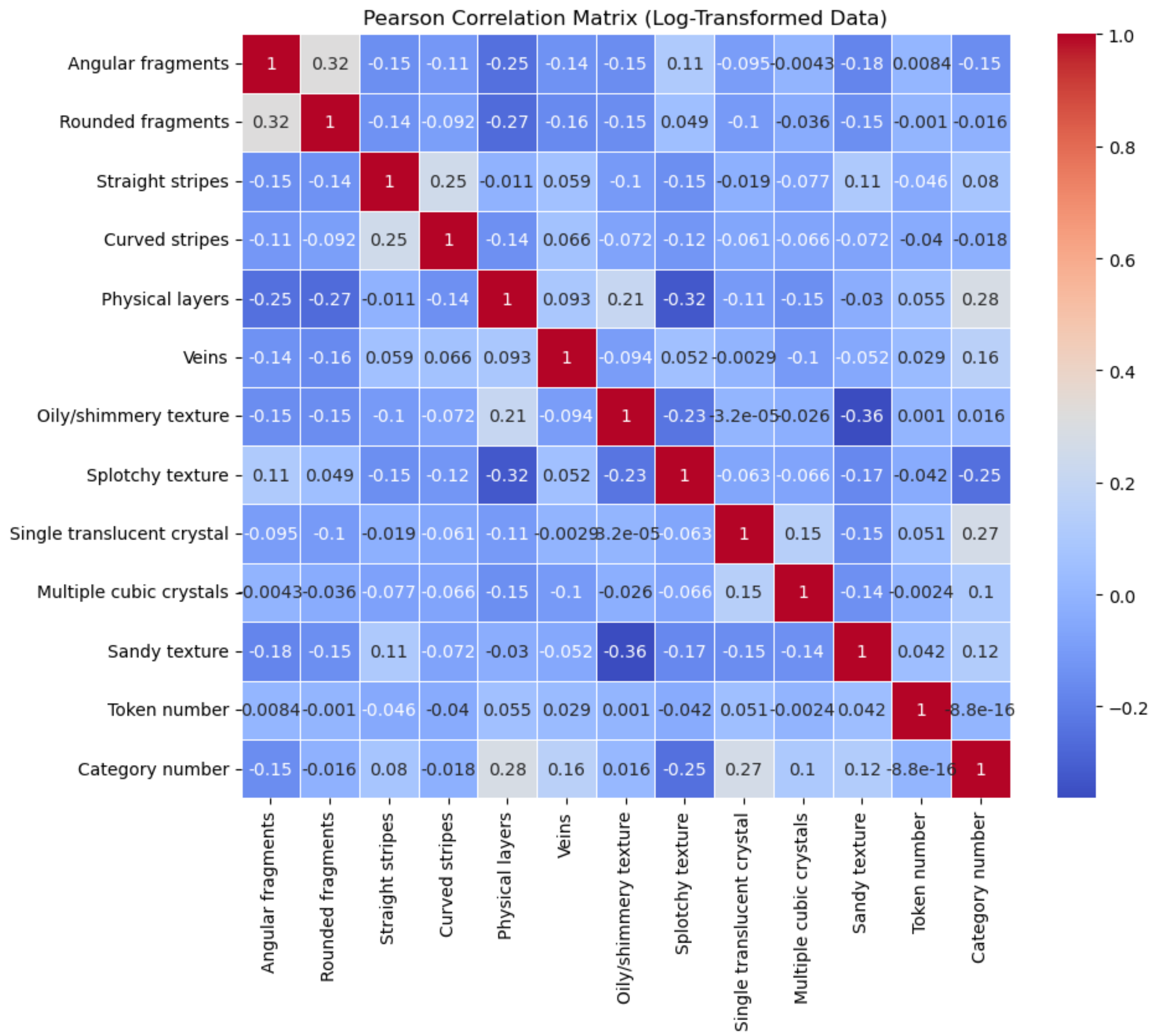


2.Analyze and discuss the relationships between the data attributes and between the data attributes and labels. This involves computing the Pearson Correlation Coefficient (PCC) and generating scatter plots.

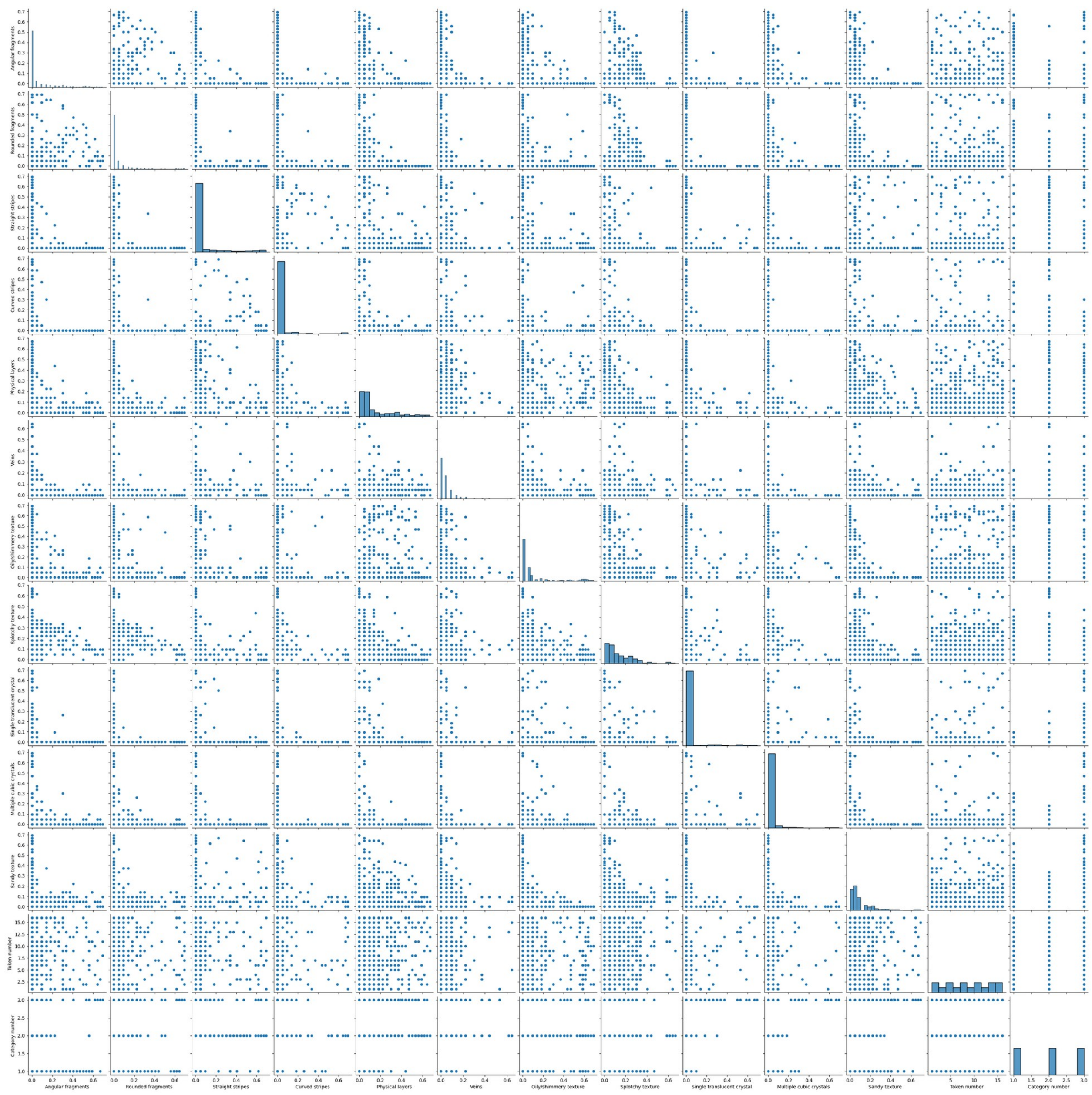
```
# Assuming the log-transformed data is already created in the previous
steps

# Compute Pearson Correlation Coefficient (PCC) for the log-
transformed data
correlation_matrix = log_transformed_data.corr(method='pearson')

# Display the correlation matrix
print("Pearson Correlation Coefficient Matrix:")
print(correlation_matrix)

# Visualize the correlation matrix using a heatmap for better
readability
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
linewidths=0.5)
plt.title("Pearson Correlation Matrix (Log-Transformed Data)")
plt.show()

# Generate scatter plots for pairs of log-transformed attributes
# Use Seaborn pairplot for scatter matrix visualization
sns.pairplot(log_transformed_data)
plt.show()

Pearson Correlation Coefficient Matrix:
                            Angular fragments  Rounded fragments  \
Angular fragments                    1.000000           0.322301
Rounded fragments                    0.322301           1.000000
Straight stripes                    -0.145704          -0.138292
Curved stripes                      -0.114815          -0.091749
Physical layers                     -0.247474          -0.267026
Veins                               -0.139829          -0.164872
Oily/shimmery texture               -0.153153          -0.150747
Splotchy texture                     0.110554           0.048664
Single translucent crystal          -0.094687          -0.104989
Multiple cubic crystals             -0.004328          -0.035588
Sandy texture                       -0.180440          -0.147915
Token number                         0.008373          -0.000998
Category number                     -0.153128          -0.015645

                            Straight stripes  Curved stripes  Physical
layers  \
Angular fragments                  -0.145704       -0.114815         -
0.247474
Rounded fragments                  -0.138292       -0.091749         -
0.267026
Straight stripes                    1.000000        0.251711         -
0.011353
Curved stripes                      0.251711        1.000000         -
0.144346
Physical layers                    -0.011353       -0.144346
1.000000
Veins                               0.058939        0.066118
0.093407
Oily/shimmery texture              -0.103484       -0.072484
0.210897
Splotchy texture                   -0.148399       -0.120758         -
0.323653
Single translucent crystal         -0.019252       -0.061164         -
0.105906
Multiple cubic crystals            -0.076794       -0.065860         -
0.147796
Sandy texture                       0.110189       -0.072025         -
0.029963
Token number                       -0.046465       -0.040164
0.054675
Category number                     0.080073       -0.017626
0.281779

                               Veins  Oily/shimmery texture  Splotchy
```

```
texture  \
Angular fragments          -0.139829               -0.153153
0.110554
Rounded fragments          -0.164872               -0.150747
0.048664
Straight stripes            0.058939               -0.103484         -
0.148399
Curved stripes              0.066118               -0.072484         -
0.120758
Physical layers             0.093407                0.210897         -
0.323653
Veins                       1.000000               -0.094412
0.052483
Oily/shimmery texture      -0.094412                1.000000         -
0.230667
Splotchy texture            0.052483               -0.230667
1.000000
Single translucent crystal -0.002893               -0.000032         -
0.062709
Multiple cubic crystals    -0.103827               -0.025695         -
0.066085
Sandy texture              -0.052009               -0.363643         -
0.171561
Token number                0.029158                0.001027         -
0.042445
Category number             0.155966                0.015916         -
0.248393

                            Single translucent crystal  \
Angular fragments                            -0.094687
Rounded fragments                            -0.104989
Straight stripes                             -0.019252
Curved stripes                               -0.061164
Physical layers                              -0.105906
Veins                                        -0.002893
Oily/shimmery texture                        -0.000032
Splotchy texture                             -0.062709
Single translucent crystal                    1.000000
Multiple cubic crystals                       0.147331
Sandy texture                                -0.154760
Token number                                  0.050863
Category number                               0.267643

                            Multiple cubic crystals  Sandy texture  \
Angular fragments                         -0.004328      -0.180440
Rounded fragments                         -0.035588      -0.147915
Straight stripes                          -0.076794       0.110189
Curved stripes                            -0.065860      -0.072025
Physical layers                           -0.147796      -0.029963
```

```
Veins                                        -0.103827      -0.052009
Oily/shimmery texture                        -0.025695      -0.363643
Splotchy texture                             -0.066085      -0.171561
Single translucent crystal                    0.147331      -0.154760
Multiple cubic crystals                       1.000000      -0.144241
Sandy texture                                -0.144241       1.000000
Token number                                 -0.002404       0.042367
Category number                               0.100021       0.124318

                            Token number  Category number
Angular fragments            8.373427e-03   -1.531279e-01
Rounded fragments           -9.983832e-04   -1.564479e-02
Straight stripes            -4.646529e-02    8.007313e-02
Curved stripes              -4.016385e-02   -1.762645e-02
Physical layers              5.467521e-02    2.817792e-01
Veins                        2.915829e-02    1.559655e-01
Oily/shimmery texture        1.027095e-03    1.591623e-02
Splotchy texture            -4.244499e-02   -2.483927e-01
Single translucent crystal   5.086293e-02    2.676429e-01
Multiple cubic crystals     -2.404321e-03    1.000213e-01
Sandy texture                4.236721e-02    1.243176e-01
Token number                 1.000000e+00   -8.829406e-16
Category number             -8.829406e-16    1.000000e+00
```



	Angular fragments	Rounded fragments	Straight stripes	Curved stripes	Physical layers	Veins	Oily/shimmery texture	Splotchy texture	Single translucent crystal	Multiple cubic crystals	Sandy texture	Token number	Category number
Angular fragments	1	0.32	-0.15	-0.11	-0.25	-0.14	-0.15	0.11	-0.095	-0.0043	-0.18	0.0084	-0.15
Rounded fragments	0.32	1	-0.14	-0.092	-0.27	-0.16	-0.15	0.049	-0.1	-0.036	-0.15	-0.001	-0.016
Straight stripes	-0.15	-0.14	1	0.25	-0.011	0.059	-0.1	-0.15	-0.019	-0.077	0.11	-0.046	0.08
Curved stripes	-0.11	-0.092	0.25	1	-0.14	0.066	-0.072	-0.12	-0.061	-0.066	-0.072	-0.04	-0.018
Physical layers	-0.25	-0.27	-0.011	-0.14	1	0.093	0.21	-0.32	-0.11	-0.15	-0.03	0.055	0.28
Veins	-0.14	-0.16	0.059	0.066	0.093	1	-0.094	0.052	-0.0029	-0.1	-0.052	0.029	0.16
Oily/shimmery texture	-0.15	-0.15	-0.1	-0.072	0.21	-0.094	1	-0.23	-3.2e-05	-0.026	-0.36	0.001	0.016
Splotchy texture	0.11	0.049	-0.15	-0.12	-0.32	0.052	-0.23	1	-0.063	-0.066	-0.17	-0.042	-0.25
Single translucent crystal	-0.095	-0.1	-0.019	-0.061	-0.11	-0.0029	-3.2e-05	-0.063	1	0.15	-0.15	0.051	0.27
Multiple cubic crystals	-0.0043	-0.036	-0.077	-0.066	-0.15	-0.1	-0.026	-0.066	0.15	1	-0.14	-0.0024	0.1
Sandy texture	-0.18	-0.15	0.11	-0.072	-0.03	-0.052	-0.36	-0.17	-0.15	-0.14	1	0.042	0.12
Token number	0.0084	-0.001	-0.046	-0.04	0.055	0.029	0.001	-0.042	0.051	-0.0024	0.042	1	-8.8e-16
Category number	-0.15	-0.016	0.08	-0.018	0.28	0.16	0.016	-0.25	0.27	0.1	0.12	-8.8e-16	1



From the PCC heatmap, we can make the following observations:

1. Strongest Positive Correlation: Angular fragments and Rounded fragments (0.32): These two attributes have the highest positive correlation in the matrix, indicating that they tend to increase together. This suggests that when a sample has more Angular fragments, it also tends to have more Rounded fragments. Physical layers and Category number (0.28): There is a moderate positive correlation between Physical layers and Category number, suggesting that the presence of more physical layers tends to be associated with certain categories.

Single translucent crystal and Category number (0.27): Similarly, Single translucent crystal is moderately positively correlated with Category number.

1. Strongest Negative Correlation: Oily/shimmery texture and Sandy texture (-0.36): This is the most negative correlation in the dataset. It suggests that samples with high Oily/shimmery texture tend to have lower Sandy texture and vice versa. These two textures may represent opposite characteristics in the samples.

Splotchy texture and Physical layers (-0.32): This indicates that as Splotchy texture increases, Physical layers tend to decrease. There may be some inverse relationship between these two characteristics in the data.

1. Weak or No Correlation: Many of the correlations are close to zero, indicating that there is little or no linear relationship between those pairs of attributes. For example: Multiple cubic crystals and Curved stripes (-0.066): This indicates almost no correlation between these two attributes.

Veins and Physical layers (0.093): This shows a weak positive correlation, indicating little linear relationship.

Attributes like Token number show almost no correlation with other features, indicating they might be irrelevant for predictive models or analysis.

1. Category Number: Category number is positively correlated with attributes like Physical layers (0.28) and Single translucent crystal (0.27), suggesting that these features may be indicative of certain categories. However, the correlations are not very strong, indicating that while these attributes are related to category, they are not the sole defining features.

3.For training data, use 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).

```
print(type(rock_df['Token number']))
train_data = log_transformed_data[log_transformed_data['Token number']
<= 10]
val_data = log_transformed_data[(log_transformed_data['Token number']
>= 11) & (log_transformed_data['Token number'] <= 13)]
test_data = log_transformed_data[log_transformed_data['Token number']
>= 14]

# Features and labels for each split
X_train = train_data.drop(columns=['Category number', 'Token number'])
y_train = train_data['Category number']

X_val = val_data.drop(columns=['Category number', 'Token number'])
y_val = val_data['Category number']

X_test = test_data.drop(columns=['Category number', 'Token number'])
y_test = test_data['Category number']

# Standardize the feature sets
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
```

```
X_val_scaled = scaler.transform(X_val)
X_test_scaled = scaler.transform(X_test)

<class 'pandas.core.series.Series'>
```

4A.Multinomial Logistic Regression (Softmax Regression); hyperparameters to explore: C, solver, max number of iterations

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, classification_report

# Step 3: Define the Logistic Regression model (Multinomial Logistic
Regression)
log_reg = LogisticRegression(multi_class='multinomial', max_iter=1000)

# Step 4: Set up hyperparameters to explore using GridSearchCV
param_grid = {
    'C': [0.01, 0.1, 1, 10, 100],  # Inverse of regularization
strength
    'solver': ['lbfgs', 'saga', 'newton-cg'],  # Solvers for multi-
class logistic regression
    'max_iter': [100, 200, 500, 1000]  # Number of iterations
}

# Step 5: Use GridSearchCV to find the best hyperparameters
grid_search = GridSearchCV(log_reg, param_grid, cv=5,
scoring='accuracy', verbose=1, n_jobs=-1)
grid_search.fit(X_train, y_train)

# Step 6: Get the best model and hyperparameters
best_model = grid_search.best_estimator_
best_params = grid_search.best_params_
print(f"Best Hyperparameters: {best_params}")

# Step 7: Evaluate performance on training data
y_train_pred = best_model.predict(X_train)
train_accuracy = accuracy_score(y_train, y_train_pred)
train_precision = precision_score(y_train, y_train_pred,
average='weighted')
train_recall = recall_score(y_train, y_train_pred, average='weighted')
train_f1 = f1_score(y_train, y_train_pred, average='weighted')

# Step 8: Evaluate performance on validation data
y_val_pred = best_model.predict(X_val)
val_accuracy = accuracy_score(y_val, y_val_pred)
val_precision = precision_score(y_val, y_val_pred, average='weighted')
val_recall = recall_score(y_val, y_val_pred, average='weighted')
val_f1 = f1_score(y_val, y_val_pred, average='weighted')
```

```
# Step 9: Evaluate performance on testing data
y_test_pred = best_model.predict(X_test)
test_accuracy = accuracy_score(y_test, y_test_pred)
test_precision = precision_score(y_test, y_test_pred,
average='weighted')
test_recall = recall_score(y_test, y_test_pred, average='weighted')
test_f1 = f1_score(y_test, y_test_pred, average='weighted')

# Step 10: Display performance results
print(f"\nTraining Performance:")
print(f"Accuracy: {train_accuracy:.4f}, Precision:
{train_precision:.4f}, Recall: {train_recall:.4f}, F1-Score:
{train_f1:.4f}")

print("\nClassification Report on Training Data:")
print(classification_report(y_train, y_train_pred))

print(f"\nValidation Performance:")
print(f"Accuracy: {val_accuracy:.4f}, Precision: {val_precision:.4f},
Recall: {val_recall:.4f}, F1-Score: {val_f1:.4f}")

print("\nClassification Report on Validation Data:")
print(classification_report(y_val, y_val_pred))

print(f"\nTesting Performance:")
print(f"Accuracy: {test_accuracy:.4f}, Precision:
{test_precision:.4f}, Recall: {test_recall:.4f}, F1-Score:
{test_f1:.4f}")

print("\nClassification Report on Testing Data:")
print(classification_report(y_test, y_test_pred))
```

```
Fitting 5 folds for each of 60 candidates, totalling 300 fits
Best Hyperparameters: {'C': 100, 'max_iter': 100, 'solver': 'lbfgs'}

Training Performance:
Accuracy: 0.6733, Precision: 0.6753, Recall: 0.6733, F1-Score: 0.6738

Classification Report on Training Data:
              precision    recall  f1-score   support

           1       0.72      0.67      0.69       100
           2       0.64      0.68      0.66       100
           3       0.67      0.67      0.67       100

    accuracy                           0.67       300
   macro avg       0.68      0.67      0.67       300
weighted avg       0.68      0.67      0.67       300
```

```
Validation Performance:
Accuracy: 0.7556, Precision: 0.7620, Recall: 0.7556, F1-Score: 0.7490

Classification Report on Validation Data:
              precision    recall  f1-score   support

           1       0.80      0.93      0.86        30
           2       0.68      0.77      0.72        30
           3       0.81      0.57      0.67        30

    accuracy                           0.76        90
   macro avg       0.76      0.76      0.75        90
weighted avg       0.76      0.76      0.75        90


Testing Performance:
Accuracy: 0.7000, Precision: 0.7160, Recall: 0.7000, F1-Score: 0.6997

Classification Report on Testing Data:
              precision    recall  f1-score   support

           1       0.78      0.60      0.68        30
           2       0.75      0.70      0.72        30
           3       0.62      0.80      0.70        30

    accuracy                           0.70        90
   macro avg       0.72      0.70      0.70        90
weighted avg       0.72      0.70      0.70        90
```

Impact of Hyperparameters

- C (Inverse of regularization strength):
  - Values tested are 0.01, 0.1, 1, 10, and 100.
  - The best-performing value was found when C is 100, indicating that the model benefited from less regularization and required more flexibility to capture patterns in the dataset effectively.
- max_iter:
  - The best value of 100 suggests that the model converges relatively quickly.
  - This could indicate that the problem is not extremely complex or that the chosen solver (lbfgs) is efficient for this dataset.
- solver (Algorithm to use in the optimization problem): The 'lbfgs' solver was selected, which is generally efficient for smaller datasets. This solver uses an approximation to the Hessian matrix to steer its search through parameter space, often leading to faster convergence.

4B.Support Vector Machine

```
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, classification_report

# Step 3: Define the Support Vector Classifier (SVC)
svm = SVC()

# Step 4: Set up the hyperparameter grid to explore
param_grid = {
    'C': [0.1, 1, 10, 100],                       # Regularization
parameter
    'kernel': ['linear', 'poly', 'rbf'],        # Kernel type
    'degree': [2, 3, 4],                          # Degree for polynomial
kernel (only used when kernel='poly')
    'gamma': ['scale', 'auto']                    # Kernel coefficient for
'rbf', 'poly' and 'sigmoid'
}

# Step 5: Use GridSearchCV for hyperparameter tuning (using 5-fold
cross-validation)
grid_search = GridSearchCV(svm, param_grid, cv=5, scoring='accuracy',
verbose=1, n_jobs=-1)
grid_search.fit(X_train, y_train)

# Step 6: Get the best model and hyperparameters
best_model = grid_search.best_estimator_
best_params = grid_search.best_params_
print(f"Best Hyperparameters: {best_params}")

# Step 7: Evaluate the performance on training data
y_train_pred = best_model.predict(X_train)
train_accuracy = accuracy_score(y_train, y_train_pred)
train_precision = precision_score(y_train, y_train_pred,
average='weighted')
train_recall = recall_score(y_train, y_train_pred, average='weighted')
train_f1 = f1_score(y_train, y_train_pred, average='weighted')

# Step 8: Evaluate the performance on validation data
y_val_pred = best_model.predict(X_val)
val_accuracy = accuracy_score(y_val, y_val_pred)
val_precision = precision_score(y_val, y_val_pred, average='weighted')
val_recall = recall_score(y_val, y_val_pred, average='weighted')
val_f1 = f1_score(y_val, y_val_pred, average='weighted')

# Step 9: Evaluate the performance on testing data
y_test_pred = best_model.predict(X_test)
test_accuracy = accuracy_score(y_test, y_test_pred)
test_precision = precision_score(y_test, y_test_pred,
average='weighted')
```

```
test_recall = recall_score(y_test, y_test_pred, average='weighted')
test_f1 = f1_score(y_test, y_test_pred, average='weighted')

# Step 10: Display performance results
print(f"\nTraining Performance:")
print(f"Accuracy: {train_accuracy:.4f}, Precision:
{train_precision:.4f}, Recall: {train_recall:.4f}, F1-Score:
{train_f1:.4f}")

print("\nClassification Report on Training Data:")
print(classification_report(y_train, y_train_pred))

print(f"\nValidation Performance:")
print(f"Accuracy: {val_accuracy:.4f}, Precision: {val_precision:.4f},
Recall: {val_recall:.4f}, F1-Score: {val_f1:.4f}")

print("\nClassification Report on Validation Data:")
print(classification_report(y_val, y_val_pred))

print(f"\nTesting Performance:")
print(f"Accuracy: {test_accuracy:.4f}, Precision:
{test_precision:.4f}, Recall: {test_recall:.4f}, F1-Score:
{test_f1:.4f}")

print("\nClassification Report on Testing Data:")
print(classification_report(y_test, y_test_pred))
```

```
Fitting 5 folds for each of 72 candidates, totalling 360 fits
Best Hyperparameters: {'C': 10, 'degree': 3, 'gamma': 'scale',
'kernel': 'poly'}

Training Performance:
Accuracy: 0.8267, Precision: 0.8349, Recall: 0.8267, F1-Score: 0.8250

Classification Report on Training Data:
              precision    recall  f1-score   support

           1       0.77      0.95      0.85       100
           2       0.87      0.73      0.79       100
           3       0.87      0.80      0.83       100

    accuracy                           0.83       300
   macro avg       0.83      0.83      0.83       300
weighted avg       0.83      0.83      0.83       300


Validation Performance:
Accuracy: 0.7667, Precision: 0.7621, Recall: 0.7667, F1-Score: 0.7605

Classification Report on Validation Data:
              precision    recall  f1-score   support
           1       0.81      0.97      0.88        30
           2       0.73      0.63      0.68        30
           3       0.75      0.70      0.72        30

    accuracy                           0.77        90
   macro avg       0.76      0.77      0.76        90
weighted avg       0.76      0.77      0.76        90


Testing Performance:
Accuracy: 0.6778, Precision: 0.6748, Recall: 0.6778, F1-Score: 0.6709

Classification Report on Testing Data:
              precision    recall  f1-score   support

           1       0.70      0.87      0.78        30
           2       0.67      0.53      0.59        30
           3       0.66      0.63      0.64        30

    accuracy                           0.68        90
   macro avg       0.67      0.68      0.67        90
weighted avg       0.67      0.68      0.67        90
```

Impact of Hyperparameters

- C (Regularization parameter):
  - The best value of 10 indicates a moderate regularization strength.
  - This suggests a balance between fitting the training data and maintaining model generalization.
- Kernel:
  - The polynomial kernel was selected which can be used for non-linear data.
- Degree:
  - A degree of 3 for the polynomial kernel suggests that the model benefits from capturing higher-order interactions between features.
  - This complexity helps in fitting the training data but may contribute to overfitting.
- Gamma:
  - The 'scale' option was chosen.
  - This adaptive approach to setting gamma can help in handling different scales of input features.

4C.Random Forest classifier

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, classification_report
```

```
# Step 3: Define the Random Forest Classifier
rf_clf = RandomForestClassifier(random_state=42)

# Step 4: Set up the hyperparameter grid to explore
param_grid = {
    'n_estimators': [50, 75, 300],
    'max_depth': [2, 7, 9, 200],
    'min_samples_split': [10, 15, 20, 80],
    'min_samples_leaf': [10, 20, 30]
}
# Step 5: Use GridSearchCV for hyperparameter tuning (using 5-fold
cross-validation)
grid_search = GridSearchCV(rf_clf, param_grid, cv=5,
scoring='accuracy', verbose=1, n_jobs=-1)
grid_search.fit(X_train, y_train)

# Step 6: Get the best model and hyperparameters
best_model = grid_search.best_estimator_
best_params = grid_search.best_params_
print(f"Best Hyperparameters: {best_params}")

feature_importances = best_model.feature_importances_
features = X.columns
importance_df = pd.DataFrame({'Feature': features, 'Importance':
feature_importances})
importance_df = importance_df.sort_values(by='Importance',
ascending=False)
# Plotting feature importance
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=importance_df)
plt.title('Feature Importance in Random Forest Classifier')
plt.show()

# Step 7: Evaluate the performance on training data
y_train_pred = best_model.predict(X_train)
train_accuracy = accuracy_score(y_train, y_train_pred)
train_precision = precision_score(y_train, y_train_pred,
average='weighted')
train_recall = recall_score(y_train, y_train_pred, average='weighted')
train_f1 = f1_score(y_train, y_train_pred, average='weighted')

# Step 8: Evaluate the performance on validation data
y_val_pred = best_model.predict(X_val)
val_accuracy = accuracy_score(y_val, y_val_pred)
val_precision = precision_score(y_val, y_val_pred, average='weighted')
val_recall = recall_score(y_val, y_val_pred, average='weighted')
val_f1 = f1_score(y_val, y_val_pred, average='weighted')

# Step 9: Evaluate the performance on testing data
```

```
y_test_pred = best_model.predict(X_test)
test_accuracy = accuracy_score(y_test, y_test_pred)
test_precision = precision_score(y_test, y_test_pred,
average='weighted')
test_recall = recall_score(y_test, y_test_pred, average='weighted')
test_f1 = f1_score(y_test, y_test_pred, average='weighted')

# Step 10: Display performance results
print(f"\nTraining Performance:")
print(f"Accuracy: {train_accuracy:.4f}, Precision:
{train_precision:.4f}, Recall: {train_recall:.4f}, F1-Score:
{train_f1:.4f}")

print("\nClassification Report on Training Data:")
print(classification_report(y_train, y_train_pred))

print(f"\nValidation Performance:")
print(f"Accuracy: {val_accuracy:.4f}, Precision: {val_precision:.4f},
Recall: {val_recall:.4f}, F1-Score: {val_f1:.4f}")

print("\nClassification Report on Validation Data:")
print(classification_report(y_val, y_val_pred))

print(f"\nTesting Performance:")
print(f"Accuracy: {test_accuracy:.4f}, Precision:
{test_precision:.4f}, Recall: {test_recall:.4f}, F1-Score:
{test_f1:.4f}")

print("\nClassification Report on Testing Data:")
print(classification_report(y_test, y_test_pred))
```

```
Fitting 5 folds for each of 144 candidates, totalling 720 fits
Best Hyperparameters: {'max_depth': 7, 'min_samples_leaf': 30,
'min_samples_split': 10, 'n_estimators': 75}

----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
Cell In[129], line 25
     22 print(f"Best Hyperparameters: {best_params}")
     24 feature_importances = best_model.feature_importances_
---> 25 features = X.columns
     26 importance_df = pd.DataFrame({'Feature': features,
'Importance': feature_importances})
     27 importance_df = importance_df.sort_values(by='Importance',
ascending=False)

NameError: name 'X' is not defined
```

IMPACT OF HYPERPARAMETER

- Number of Estimators (n_estimators) The optimal value of 300 trees suggests that the model benefits from a large ensemble. This helps in reducing variance and improving generalization. The high number of trees likely contributes to the model's stability across different datasets.

- Maximum Depth (max_depth) A max_depth of 7 indicates that the model performs best with moderately deep trees. This depth allows the model to capture complex patterns without overfitting. It's a good balance between model complexity and generalization.

- Minimum Samples Split (min_samples_split) The value of 10 for min_samples_split means that a node will only be split if it contains at least 10 samples. This relatively low value allows for more granular splits, potentially capturing finer details in the data.

Minimum Samples Leaf (min_samples_leaf) With min_samples_leaf set to 20, each leaf node must contain at least 20 samples. This higher value helps prevent overfitting by ensuring that leaf nodes represent a significant portion of the data, not just noise or outliers.

MODEL PERFORMANCE

- The model's performance with respect to train, val and test set are 0.59, 0.58 and 0.60 respectively.
- Class 1 and 2 a performed well with the model than Class 3.

5.Combine your classifiers into an ensemble and try to outperform each individual classifier on the validation set. Once you have found a good one, try it on the test set. Describe and discuss your findings.

```
from sklearn.ensemble import VotingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, classification_report

log_reg = LogisticRegression(C= 1, max_iter= 100, solver = 'newton-
cg', random_state=42)
svm = SVC(C = 100, degree = 3, gamma = 'scale', kernel =
'poly',probability=True, random_state=42)
rf_clf = RandomForestClassifier(max_depth = 9, min_samples_leaf = 10,
min_samples_split=10, n_estimators =  100, random_state=42)

# Step 4: Combine classifiers using VotingClassifier
ensemble_clf = VotingClassifier(
    estimators=[('log_reg', log_reg), ('svm', svm), ('rf_clf',
rf_clf)],
    voting='soft'  # Use soft voting to average probabilities
)
```

```python
# Step 5: Fit the ensemble classifier on the training data
ensemble_clf.fit(X_train, y_train)

# Step 6: Evaluate the performance on training data
y_train_pred = ensemble_clf.predict(X_train)
train_accuracy = accuracy_score(y_train, y_train_pred)
train_precision = precision_score(y_train, y_train_pred,
average='weighted')
train_recall = recall_score(y_train, y_train_pred, average='weighted')
train_f1 = f1_score(y_train, y_train_pred, average='weighted')

# Step 7: Evaluate the performance on validation data
y_val_pred = ensemble_clf.predict(X_val)
val_accuracy = accuracy_score(y_val, y_val_pred)
val_precision = precision_score(y_val, y_val_pred, average='weighted')
val_recall = recall_score(y_val, y_val_pred, average='weighted')
val_f1 = f1_score(y_val, y_val_pred, average='weighted')

# Step 8: Evaluate the performance on testing data
y_test_pred = ensemble_clf.predict(X_test)
test_accuracy = accuracy_score(y_test, y_test_pred)
test_precision = precision_score(y_test, y_test_pred,
average='weighted')
test_recall = recall_score(y_test, y_test_pred, average='weighted')
test_f1 = f1_score(y_test, y_test_pred, average='weighted')

# Step 9: Display performance results
print(f"\nTraining Performance of Ensemble:")
print(f"Accuracy: {train_accuracy:.4f}, Precision:
{train_precision:.4f}, Recall: {train_recall:.4f}, F1-Score:
{train_f1:.4f}")

print("\nClassification Report on Training Data:")
print(classification_report(y_train, y_train_pred))

print(f"\nValidation Performance of Ensemble:")
print(f"Accuracy: {val_accuracy:.4f}, Precision: {val_precision:.4f},
Recall: {val_recall:.4f}, F1-Score: {val_f1:.4f}")

print("\nClassification Report on Validation Data:")
print(classification_report(y_val, y_val_pred))

print(f"\nTesting Performance of Ensemble:")
print(f"Accuracy: {test_accuracy:.4f}, Precision:
{test_precision:.4f}, Recall: {test_recall:.4f}, F1-Score:
{test_f1:.4f}")

print("\nClassification Report on Testing Data:")
print(classification_report(y_test, y_test_pred))
```

```
Training Performance of Ensemble:
Accuracy: 0.7933, Precision: 0.7959, Recall: 0.7933, F1-Score: 0.7931

Classification Report on Training Data:
              precision    recall  f1-score   support

           1       0.79      0.85      0.82       100
           2       0.75      0.79      0.77       100
           3       0.84      0.74      0.79       100

    accuracy                           0.79       300
   macro avg       0.80      0.79      0.79       300
weighted avg       0.80      0.79      0.79       300


Validation Performance of Ensemble:
Accuracy: 0.7000, Precision: 0.6932, Recall: 0.7000, F1-Score: 0.6941

Classification Report on Validation Data:
              precision    recall  f1-score   support

           1       0.77      0.90      0.83        30
           2       0.63      0.57      0.60        30
           3       0.68      0.63      0.66        30

    accuracy                           0.70        90
   macro avg       0.69      0.70      0.69        90
weighted avg       0.69      0.70      0.69        90


Testing Performance of Ensemble:
Accuracy: 0.7111, Precision: 0.7129, Recall: 0.7111, F1-Score: 0.7103

Classification Report on Testing Data:
              precision    recall  f1-score   support

           1       0.71      0.80      0.75        30
           2       0.78      0.70      0.74        30
           3       0.66      0.63      0.64        30

    accuracy                           0.71        90
   macro avg       0.71      0.71      0.71        90
weighted avg       0.71      0.71      0.71        90
```

The Voting Classifier ensemble performs the best, followed closely by Logistic Regression, then SVM, and finally Random Forest.

6.Is your method better than a human? Test that by taking human data from trialData.csv Download trialData.csv(see hereLinks to an external site. for a description of the file).

Compute human accuracy on train and test data (use only rocks with numbers 1 to 480 and note that Block number 1-3 is training, number 4 is test). How does the human accuracy compare to the accuracy of your best model? [2 points] Compute the average human accuracy and standard deviation for each of the 480 rocks (regardless of whether they are train or test rocks). Make a plot with the x-axis showing average human accuracy (values between 0 and 1) and y-axis showing model probability (also values between 0 and 1) for 480 rocks (regardless of whether they were used for train or test). Each rock should be represented with a dot in this plot. Color rocks from three different categories in different colors. [2 points] Compute the correlation coefficient between average human accuracies and model probabilities for each rock category (120 rocks per category) and for all rocks (all 480 rocks). Report the p-value. Is the correlation significant?

```
import pandas as pd
import matplotlib.pyplot as plt
from scipy.stats import pearsonr

# Load the data
human_data = pd.read_csv(r'C:\Users\charu\Downloads\trialData.csv')  # 
Replace with the correct path
rock_data = pd.read_csv(r'C:\Users\charu\Downloads\rock_df.csv')     # 
Replace with the correct path

# Filter for rocks with numbers 1 to 480
human_data = human_data[human_data['rocknumber'].between(1, 480)]


train_data = human_data[human_data['block'].isin([1, 2, 3])]
test_data = human_data[human_data['block'] == 4]

train_human_accuracy = train_data['cat_correct'].mean()
test_human_accuracy = test_data['cat_correct'].mean()
print("Human Accuracy - Train:", train_human_accuracy)
print("Human Accuracy - Test:", test_human_accuracy)

Human Accuracy - Train: 0.5599349490660221
Human Accuracy - Test: 0.5984143924378716
```

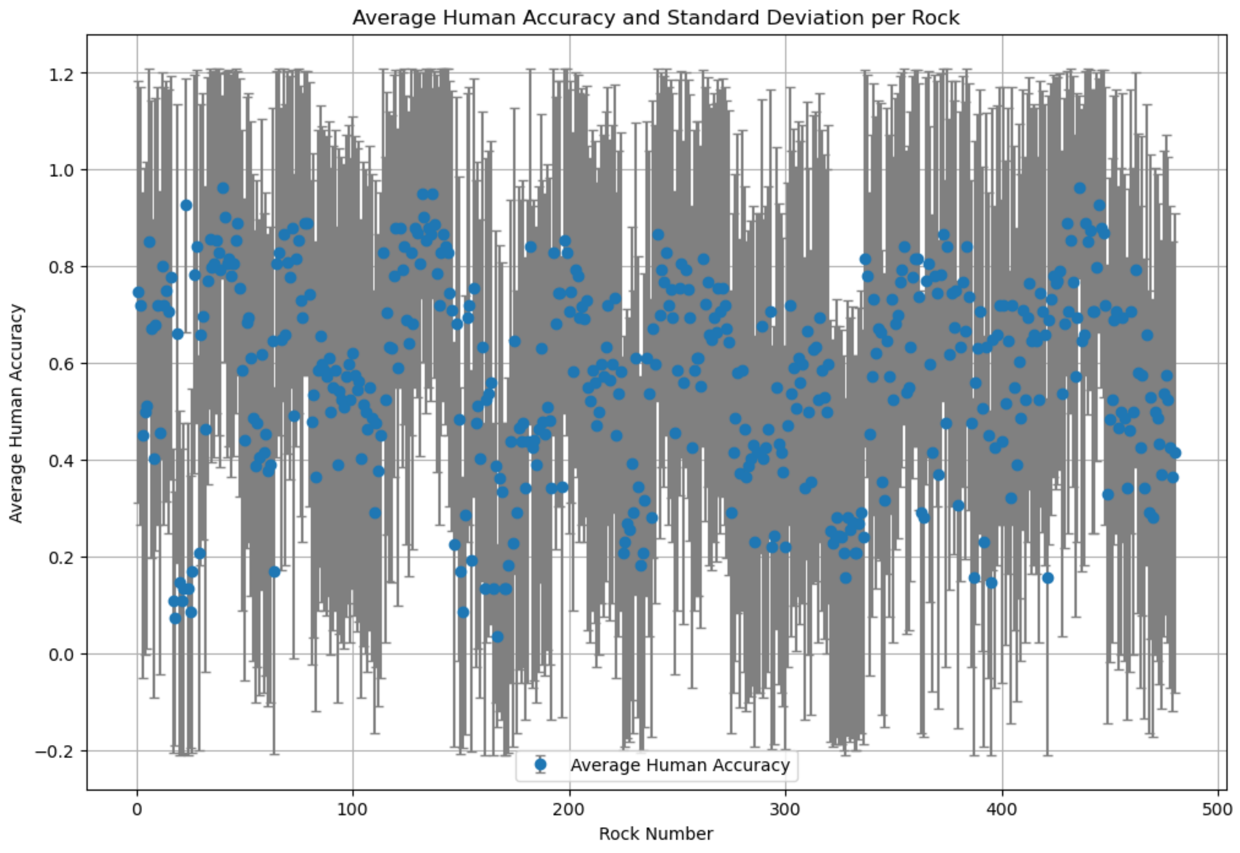
Compute human accuracy on train and test data

```
# Filter for rocks with Token numbers 1 to 10 for training and 11 to 
16 for testing in model data
X_train = rock_data[rock_data['Token number'].between(1, 
10)].drop(["Category number", "Token number"], axis=1)
y_train = rock_data[rock_data['Token number'].between(1, 10)]
['Category number']

X_test = rock_data[rock_data['Token number'].between(11, 
16)].drop(["Category number", "Token number"], axis=1)
y_test = rock_data[rock_data['Token number'].between(11, 16)]
['Category number']
```

```
# Model accuracy on train and test data
model_train_accuracy = ensemble_clf.score(X_train, y_train)
model_test_accuracy = ensemble_clf.score(X_test, y_test)
print("Model Accuracy - Train:", model_train_accuracy)
print("Model Accuracy - Test:", model_test_accuracy)
```

```
Model Accuracy - Train: 0.8
Model Accuracy - Test: 0.7
```

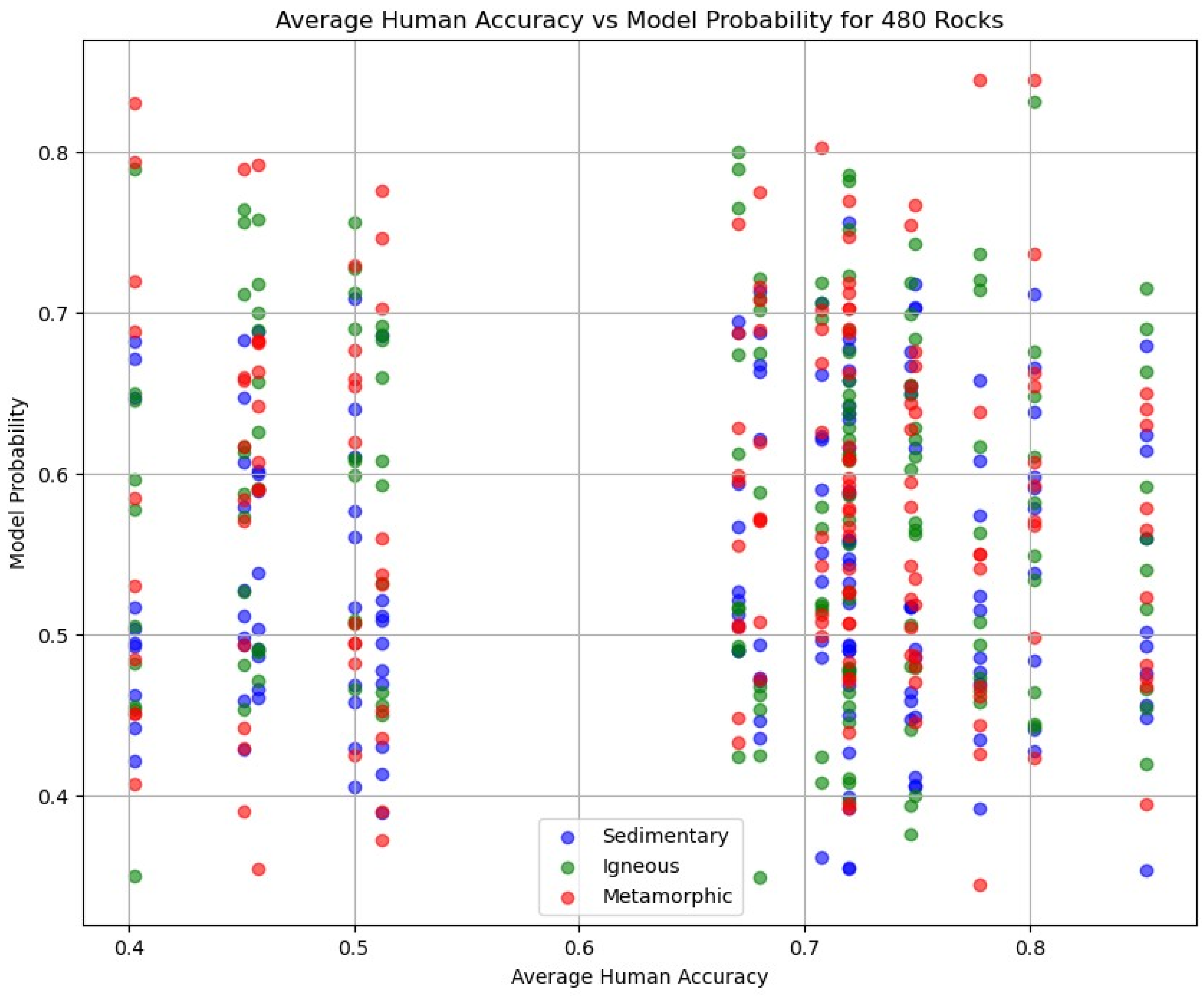
```
# 3. Compute Average Human Accuracy and Standard Deviation for Each of
the 480 Rocks
human_rock_stats = human_data.groupby('rocknumber')
['cat_correct'].agg(['mean', 'std']).rename(columns={'mean':
'average_human_accuracy', 'std': 'std_human_accuracy'})

# Plot average human accuracy and standard deviation per rock
plt.figure(figsize=(12, 8))
plt.errorbar(human_rock_stats.index,
human_rock_stats['average_human_accuracy'],
             yerr=human_rock_stats['std_human_accuracy'], fmt='o',
ecolor='gray', capsize=3, label='Average Human Accuracy')
plt.xlabel('Rock Number')
plt.ylabel('Average Human Accuracy')
plt.title('Average Human Accuracy and Standard Deviation per Rock')
plt.legend()
plt.grid(True)
plt.show()
```



```
# 4. Plot Average Human Accuracy vs Model Probability
# Assuming the model probabilities are based on predictions made for
all 480 rocks

# Make predictions and calculate the probability of the predicted
class
X_full = rock_data.drop(["Category number", "Token number"], axis=1)
# Adjust to keep only feature columns
model_probabilities = ensemble_clf.predict_proba(X_full).max(axis=1)
# Max probability for the predicted class

# Add model probabilities to rock_data
rock_data['model_probability'] = model_probabilities
rock_data['rocknumber'] = rock_data['Token number']  # Map token
number to rock number

# Merge human accuracy with model probabilities
combined_stats = human_rock_stats.merge(rock_data[['rocknumber',
'Category number', 'model_probability']],
                                        on='rocknumber', how='left')

# Define category colors
categories = {1: 'Sedimentary', 2: 'Igneous', 3: 'Metamorphic'}
colors = {'Sedimentary': 'blue', 'Igneous': 'green', 'Metamorphic':
```

```
'red'}
combined_stats['Category Name'] = combined_stats['Category
number'].map(categories)

plt.figure(figsize=(10, 8))
for category in colors:
    category_data = combined_stats[combined_stats['Category Name'] ==
category]
    plt.scatter(category_data['average_human_accuracy'],
category_data['model_probability'],
                label=category, color=colors[category], alpha=0.6)
plt.xlabel('Average Human Accuracy')
plt.ylabel('Model Probability')
plt.title('Average Human Accuracy vs Model Probability for 480 Rocks')
plt.legend()
plt.grid(True)
plt.show()

# 5. Drop rows with NaN values in either 'average_human_accuracy' or
'model_probability' before correlation
combined_stats_cleaned =
combined_stats.dropna(subset=['average_human_accuracy',
'model_probability'])

# Compute Correlation Coefficients for Each Category and Overall
correlations = {}
for category in colors.keys():
    category_data =
combined_stats_cleaned[combined_stats_cleaned['Category Name'] ==
category]
    if len(category_data) >= 2:  # Check if there are enough data
points
        corr, p_value =
pearsonr(category_data['average_human_accuracy'],
category_data['model_probability'])
        correlations[category] = {'correlation': corr, 'p-value':
p_value}
    else:
        correlations[category] = {'correlation': None, 'p-value':
None}  # Not enough data

# Overall correlation across all rocks
if len(combined_stats_cleaned) >= 2:
    overall_corr, overall_p_value =
pearsonr(combined_stats_cleaned['average_human_accuracy'],
combined_stats_cleaned['model_probability'])
    correlations['Overall'] = {'correlation': overall_corr, 'p-value':
overall_p_value}
else:
    correlations['Overall'] = {'correlation': None, 'p-value': None}
```

```
# Not enough data

# Display correlation results
for category, stats in correlations.items():
    if stats['correlation'] is not None:
        print(f"{category} - Correlation: {stats['correlation']}, p-
value: {stats['p-value']}")
    else:
        print(f"{category} - Not enough data for correlation
calculation.")
```



```
Sedimentary - Correlation: 0.04302716795010746, p-value:
0.5890326744776714
Igneous - Correlation: -0.08248282109838448, p-value:
0.29977225792409357
Metamorphic - Correlation: -0.04200092614867484, p-value:
0.5979564054966793
```

```
Overall - Correlation: -0.030418176181366448, p-value:
0.5061495520865529
```

CONCLUSION

- The model performs significantly better than humans on the training and testing datasets, achieving higher accuracy on both sets. This suggests that the model has learned patterns in the data that allow it to classify rocks more accurately than humans.
- Human performance varies significantly across rocks, as indicated by the high variability (large error bars) in many cases plot 1. Some rocks have consistently high accuracy, while others are more challenging for humans, as indicated by lower average accuracy and larger deviations.
- The model outperforms human accuracy on the rock classification task and does not make similar errors as humans plot 2. The low correlation between human accuracy and model probability across rock categories further emphasizes that the model and human assessment differ in terms of confidence and difficulty for specific rocks.