# lgfebbquh

October 22, 2023

[ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score
from sklearn.ensemble import VotingClassifier
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score
import warnings
warnings.filterwarnings('ignore')
```

[ ]:
```
# Load the data
labels_df = pd.read_excel('aggregateRockData.xlsx', usecols=[1], header=None)
labels_df.columns = ['Category']

attributes_df = pd.read_csv('norm540.txt', sep='\t', usecols=range(3, 22),␣
 ↪header=None)
attributes_df.columns = list('abcdefghijklmnopqrs')

# Combine the data
rock_df = pd.concat([labels_df, attributes_df], axis=1)

# Display statistical values
print(rock_df.head())
```

```
  Category         a         b         c         d         e         f  \
0          1  1.690468 -0.159688 -0.646115 -0.252007 -0.609794  0.579927
1          1  1.690468 -0.159688 -0.530724  0.127922 -0.482150  2.865772
2          1  1.665576 -0.407623  0.858984 -0.631936 -0.443857  2.611790
3          1  2.233118 -0.407623 -0.415333 -0.424702 -1.120369  0.071962
4          1  2.213204 -0.159688  1.129901 -0.044773 -1.082076  1.341876

          g         h         i         j         k         l         m  \
0  0.375313 -0.352386 -0.260224 -0.759128 -0.013842 -0.540653  0.946521
1  0.375313 -0.352386 -0.260224 -0.529150 -0.512160 -0.540653 -0.249084
2 -0.405184 -0.352386 -0.260224 -0.529150 -0.512160 -0.540653  1.245422
3  4.017633 -0.352386 -0.260224 -0.529150 -0.512160 -0.540653 -0.249084
4  3.757467 -0.352386 -0.260224 -0.759128 -0.512160 -0.540653 -0.249084

          n         o         p         q         r         s
0 -0.227922 -0.225045 -0.116312  0.635812 -0.409247 -0.310419
1 -0.227922  0.185510 -0.401124  2.042938 -0.409247 -0.034059
2 -0.227922 -0.225045 -0.401124  1.665865 -0.409247 -0.310419
3 -0.227922 -0.225045 -0.116312  2.640737 -0.409247 -0.310419
4 -0.227922 -0.225045 -0.401124  2.659131 -0.409247 -0.310419
```

Q1- Statistical descriptions and Visualizations

[ ]:
```
#print the dimension
print("\n The shape of the dataframe is " , rock_df.shape)
#print all columns
print("\n The columns that are present in the dataframe" , rock_df.columns)
#view the first 5 rows of the datafram
print("\n The first five rows of the dataframe :" )
rock_df.head(5)
```

```
 The shape of the dataframe is  (540, 20)

 The columns that are present in the dataframe Index(['Category', 'a', 'b', 'c',
'd', 'e', 'f', 'g', 'h', 'i', 'j', 'k', 'l',
       'm', 'n', 'o', 'p', 'q', 'r', 's'],
      dtype='object')

 The first five rows of the dataframe :
```

[ ]:
```
   Category         a         b         c         d         e         f  \
0         1  1.690468 -0.159688 -0.646115 -0.252007 -0.609794  0.579927
1         1  1.690468 -0.159688 -0.530724  0.127922 -0.482150  2.865772
2         1  1.665576 -0.407623  0.858984 -0.631936 -0.443857  2.611790
3         1  2.233118 -0.407623 -0.415333 -0.424702 -1.120369  0.071962
4         1  2.213204 -0.159688  1.129901 -0.044773 -1.082076  1.341876

          g         h         i         j         k         l         m  \
0  0.375313 -0.352386 -0.260224 -0.759128 -0.013842 -0.540653  0.946521
1  0.375313 -0.352386 -0.260224 -0.529150 -0.512160 -0.540653 -0.249084
2 -0.405184 -0.352386 -0.260224 -0.529150 -0.512160 -0.540653  1.245422
3  4.017633 -0.352386 -0.260224 -0.529150 -0.512160 -0.540653 -0.249084
4  3.757467 -0.352386 -0.260224 -0.759128 -0.512160 -0.540653 -0.249084

          n         o         p         q         r         s
0 -0.227922 -0.225045 -0.116312  0.635812 -0.409247 -0.310419
1 -0.227922  0.185510 -0.401124  2.042938 -0.409247 -0.034059
2 -0.227922 -0.225045 -0.401124  1.665865 -0.409247 -0.310419
3 -0.227922 -0.225045 -0.116312  2.640737 -0.409247 -0.310419
4 -0.227922 -0.225045 -0.401124  2.659131 -0.409247 -0.310419
```

```
[ ]: #Let's calculate the percentage of missing values in each column.
     perc_missing = pd.DataFrame((rock_df.isna().sum()/len(rock_df)) * 100,columns =␣
      ↪["Perecentage Missing"])
     perc_missing
```

```
[ ]:           Perecentage Missing
     Category                  0.0
     a                         0.0
     b                         0.0
     c                         0.0
     d                         0.0
     e                         0.0
     f                         0.0
     g                         0.0
     h                         0.0
     i                         0.0
     j                         0.0
     k                         0.0
     l                         0.0
     m                         0.0
     n                         0.0
     o                         0.0
     p                         0.0
     q                         0.0
     r                         0.0
     s                         0.0
```

```
[ ]: rock_df.columns
```

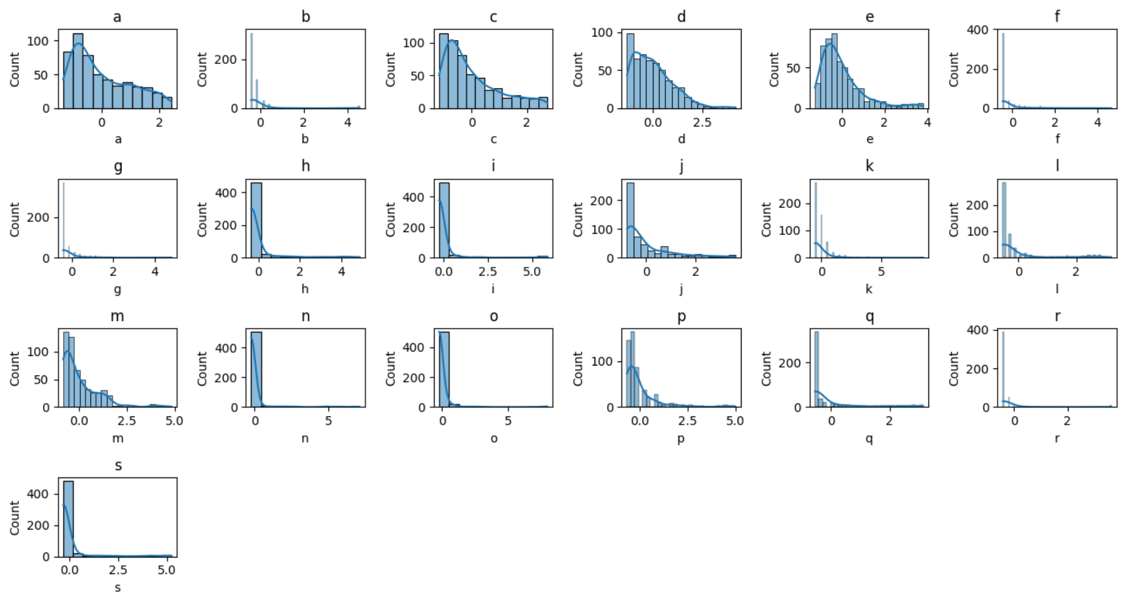
```
[ ]: Index(['Category', 'a', 'b', 'c', 'd', 'e', 'f', 'g', 'h', 'i', 'j', 'k', 'l',
            'm', 'n', 'o', 'p', 'q', 'r', 's'],
           dtype='object')
```

```
[ ]: rock_df["Category"].value_counts()
```

[ ]:
```
1    180
2    180
3    180
Name: Category, dtype: int64
```

[ ]:
```python
def display_statistics_and_histograms(df):
    stats_data = []

    # Create a single figure for all histograms
    plt.figure(figsize=(13, 7))

    for i, col in enumerate(df.columns[1:], start=1):
        stats = df[col].describe()
        median = df[col].median()
        skew = df[col].skew()
        kurt = df[col].kurt()
        stats_data.append([col, stats['mean'], median, skew, kurt])

        plt.subplot(4, 6, i)
        sns.histplot(df[str(col)], kde=True)
        plt.title(f"{col}")

    plt.tight_layout()
    plt.show()

    stats_table = pd.DataFrame(stats_data, columns=['Attribute', 'Mean',␣
↪'Median', 'Skew', 'Kurt'])
    print(stats_table)
```

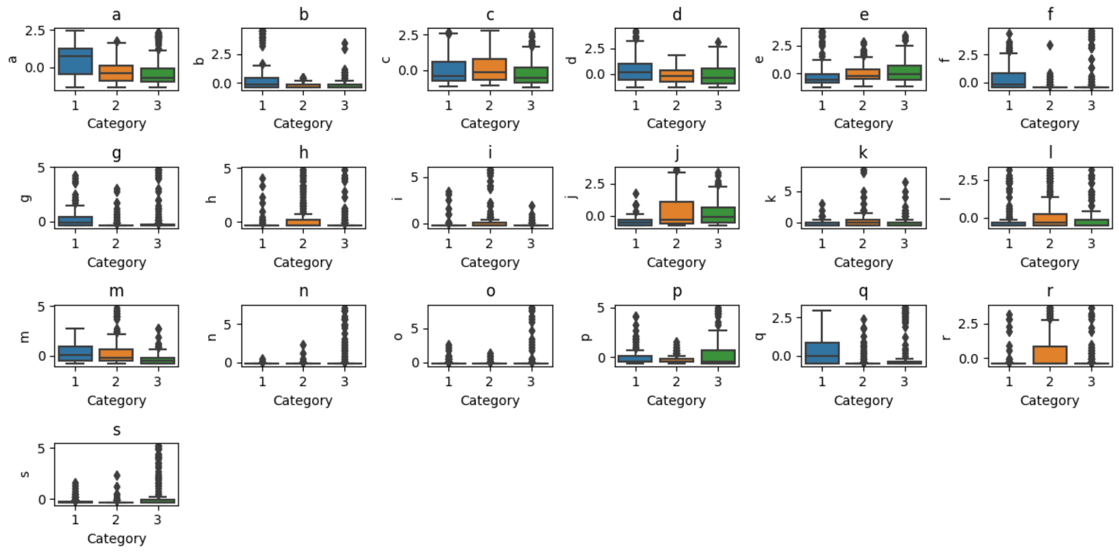
[ ]:
```python
display_statistics_and_histograms(rock_df)
```



```
   Attribute          Mean    Median      Skew       Kurt
0          a -1.851852e-09 -0.300910  0.714977  -0.671929
1          b  9.629630e-08 -0.407623  3.620303  12.602147
2          c  5.370370e-08 -0.375197  1.097902   0.230668
3          d -6.296296e-08 -0.182929  1.039908   1.220311
4          e -4.074074e-08 -0.271538  1.715341   3.113322
5          f -1.537037e-07 -0.436004  2.813088   7.566127
6          g -1.666667e-08 -0.405184  3.380080  11.557374
7          h -1.814815e-07 -0.352386  3.384711  10.969463
8          i -1.481481e-08 -0.260224  4.753846  22.632414
9          j -1.166667e-07 -0.299173  1.739787   2.501931
10         k -1.629630e-07 -0.512160  4.845069  31.612381
11         l  1.703704e-07 -0.540653  2.003191   2.622970
12         m -6.851852e-08 -0.249084  1.944237   4.770206
13         n -5.555556e-09 -0.227922  5.221579  27.935174
14         o  3.388889e-07 -0.225045  6.373542  43.200038
15         p  1.203704e-07 -0.401124  2.786519   8.787105
16         q -1.148148e-07 -0.541391  1.918221   2.425974
17         r -1.759259e-07 -0.409247  2.632849   5.617292
18         s  3.018519e-07 -0.310419  3.911822  14.875974
```

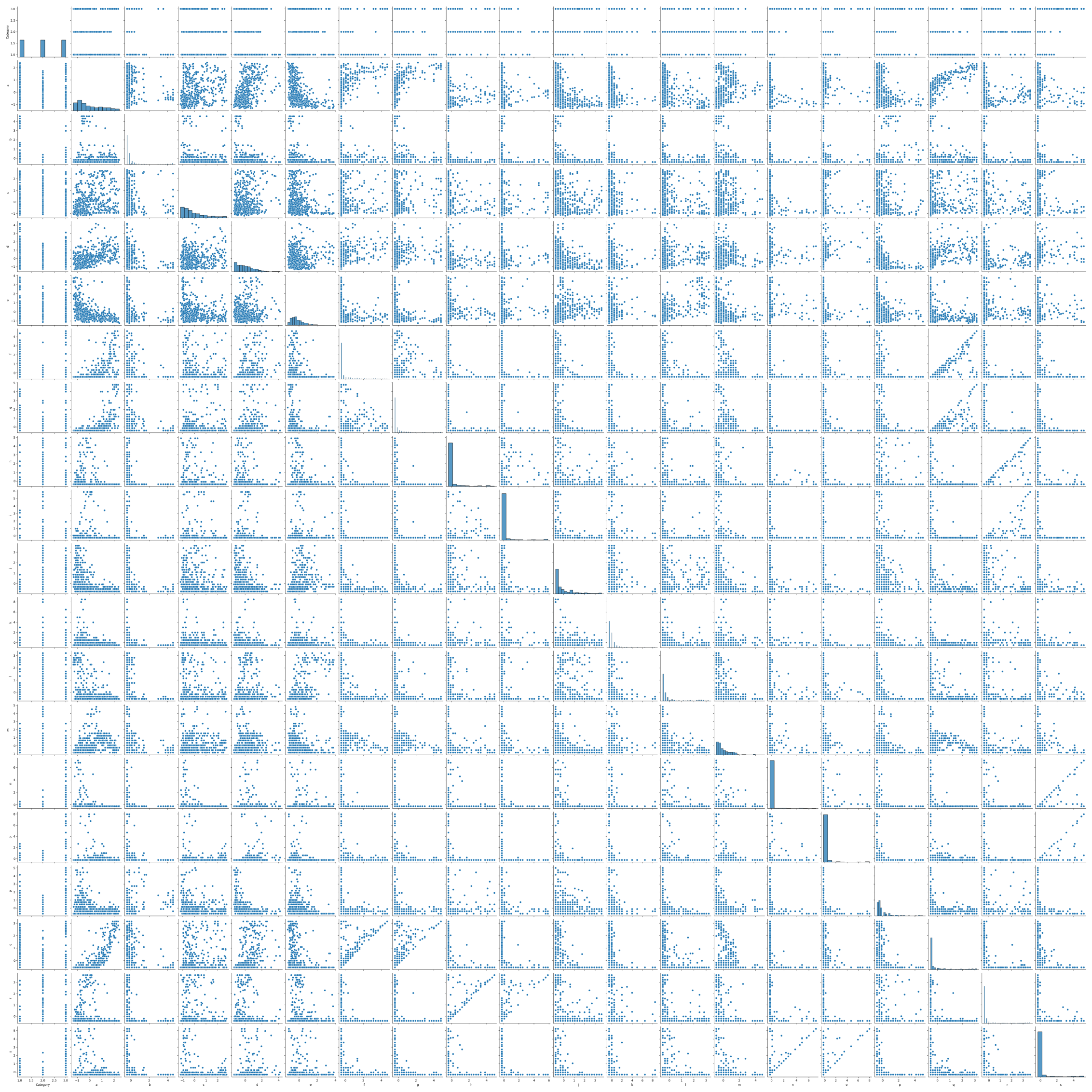
[ ]:
```python
def display_classification_insights(df):
    stats_data = []

    # Create a single figure for all histograms
    plt.figure(figsize=(12, 6))

    target_column = df.columns[0]  # Assuming the first column is the target␣
 ↪variable

    for i, col in enumerate(df.columns[1:], start=1):
        stats = df[col].describe()
        median = df[col].median()
        skew = df[col].skew()
        kurt = df[col].kurt()
        null_values = df[col].isnull().sum()

        # Boxplot for attribute with respect to the target variable
        plt.subplot(4, 6, i)
        sns.boxplot(x=target_column, y=col, data=df)
        plt.title(f"{col}")

    plt.tight_layout()
    plt.show()
```

```
display_classification_insights(rock_df)
```



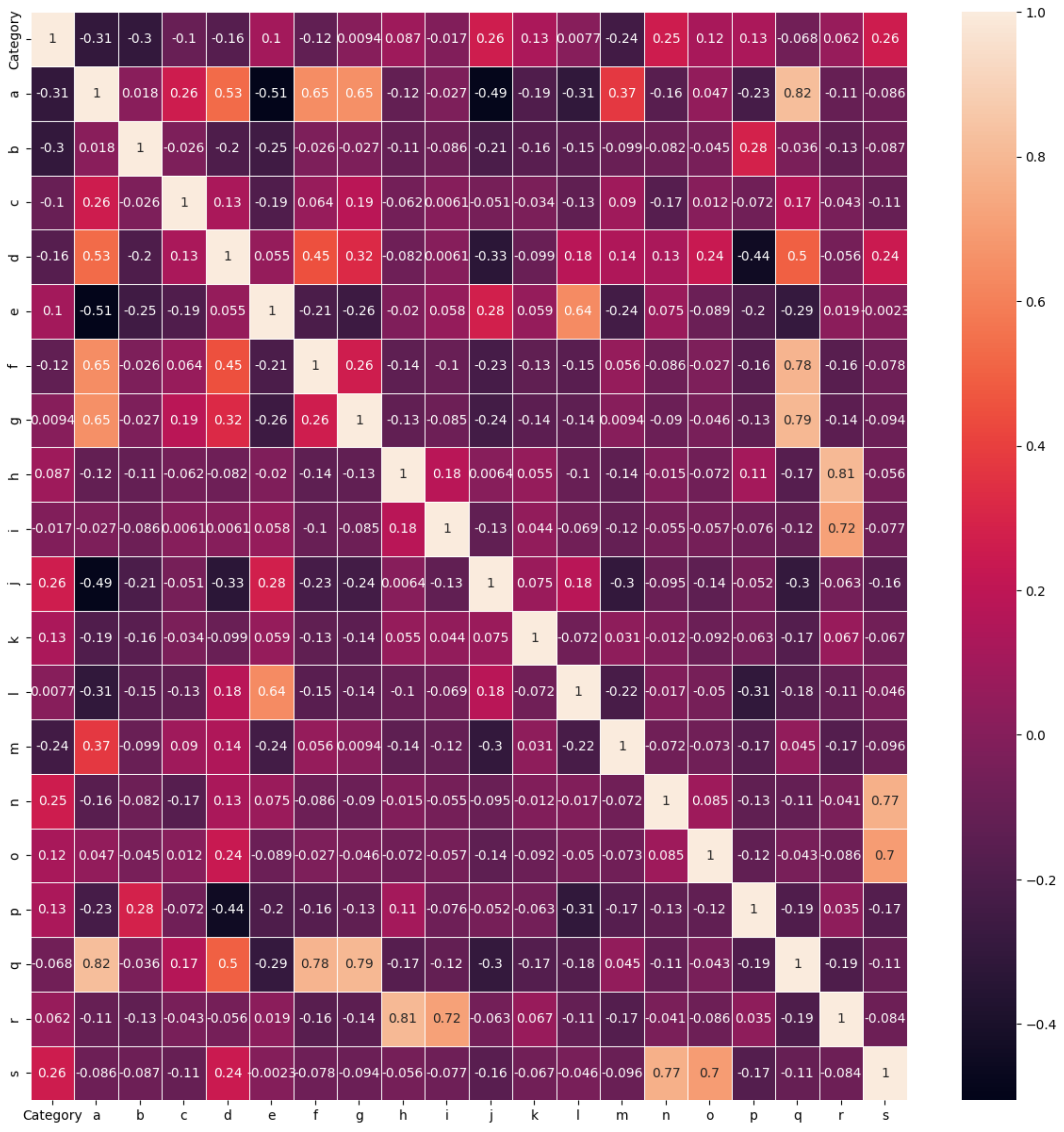
```
[ ]: #scatter plot between features
     sns.pairplot(data=rock_df)
```

```
[ ]: <seaborn.axisgrid.PairGrid at 0x7909e9bb08b0>
```



```
[ ]: fig, ax = plt.subplots(figsize=(15,15))          # Sample figsize in inches
     sns.heatmap(rock_df.corr(numeric_only=True), annot=True, linewidths=.5, ax=ax)
```

```
[ ]: <Axes: >
```



Q2- Computing the PCC:

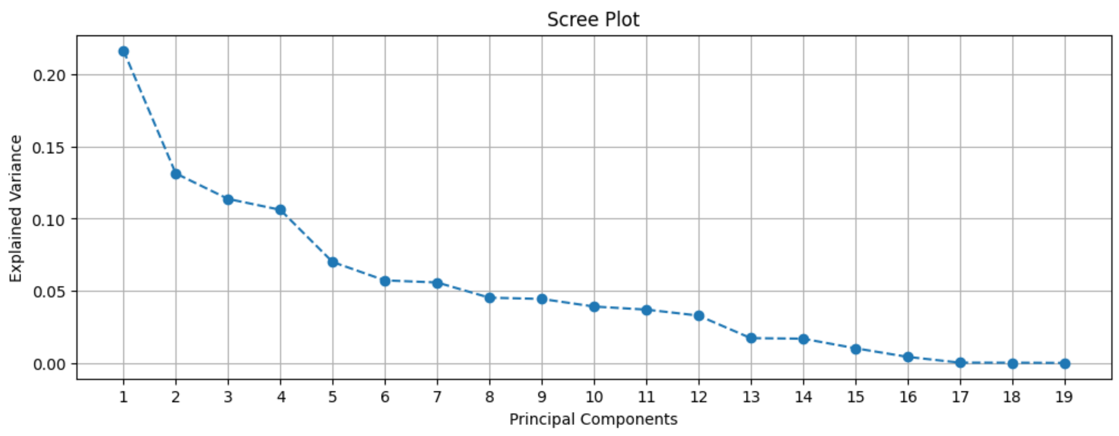
```
[ ]: corr_matrix = rock_df.corr(method="pearson",numeric_only = True)
     corr_matrix["Category"].sort_values(ascending = False)
```

```
[ ]: Category     1.000000
     j            0.262855
     s            0.258386
     n            0.253550
     p            0.132240
     k            0.130094
```

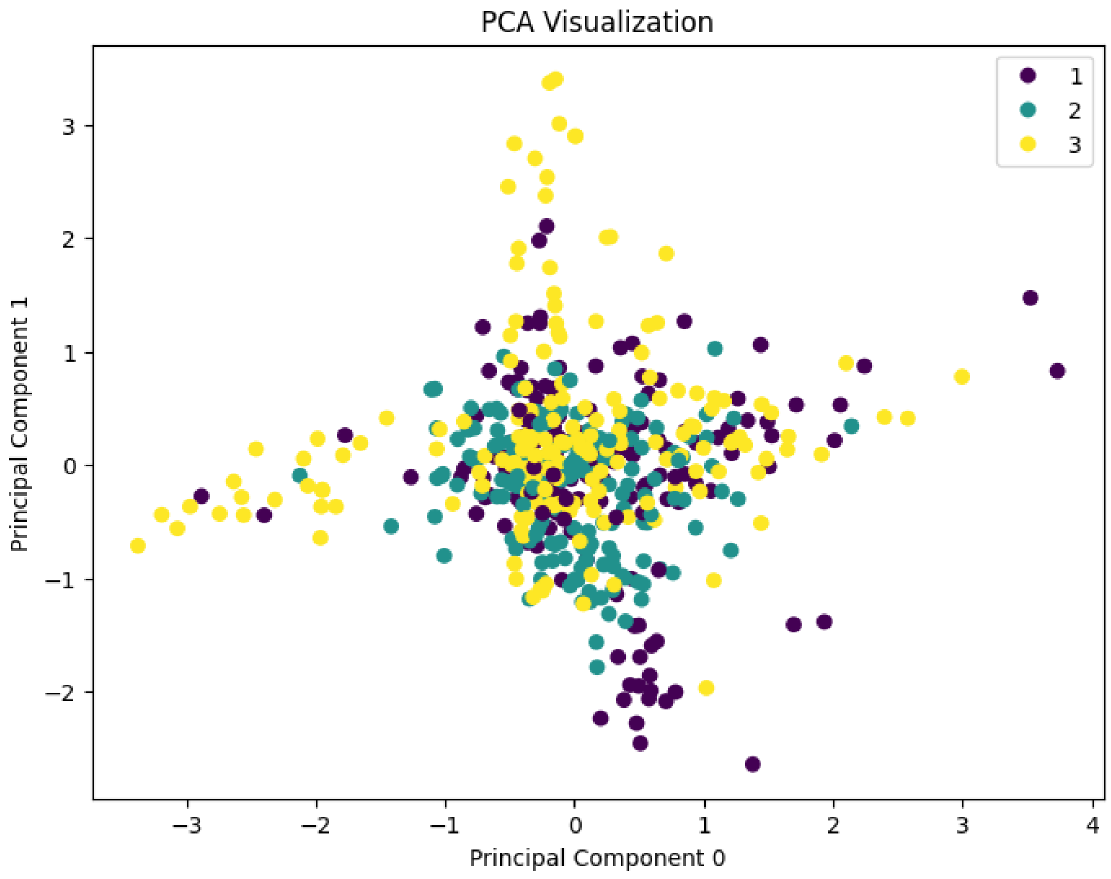
```
o           0.121163
e           0.103781
h           0.086923
r           0.061825
g           0.009450
l           0.007679
i          -0.016680
q          -0.068022
c          -0.104748
f          -0.123388
d          -0.164925
m          -0.242921
b          -0.301462
a          -0.305296
Name: Category, dtype: float64
```

Special treatment:Given the substantial quantity of attributes we need to manage before feeding the data to algorithms, PCA is employed to address this issue.

```
[ ]: # Separate labels and attributes
     X = rock_df.iloc[:, 1:]   # Features (attributes)
     y = rock_df['Category']   # Labels

     # Standardize the data (important for PCA)
     scaler = StandardScaler()
     X_scaled = scaler.fit_transform(X)

     # Perform PCA
     pca = PCA()
     X_pca = pca.fit_transform(X_scaled)

     # Variance explained by each component
     explained_variance = pca.explained_variance_ratio_

     # Create a custom range with more points on the x-axis
     x = range(1, len(explained_variance) + 1)  # This is your current x-axis range
     custom_x = range(1, len(explained_variance) + 1, 1)  # Adjust the step value (5␣
      ↪in this example)

     plt.figure(figsize=(12, 4))  # Adjust the figure size as needed
     plt.plot(x, explained_variance, marker='o', linestyle='--')

     # Set custom x-ticks and labels
     plt.xticks(custom_x)
     plt.xlabel('Principal Components')
     plt.ylabel('Explained Variance')
     plt.title('Scree Plot')
     plt.grid()

     plt.show()

     # Choose the number of components based on explained variance
     cumulative_explained_variance = explained_variance.cumsum()
     n_components = 0
     for i, explained_var in enumerate(cumulative_explained_variance):
         if explained_var >= 0.95:
             n_components = i + 1
             break

     print(f"Number of components to keep 95% variance: {n_components}")

     # Perform PCA with the selected number of components
     pca = PCA(n_components)
     X_pca = pca.fit_transform(X_scaled)


     # Visualize the data in the reduced dimension
     plt.figure(figsize=(8, 6))
     plot= plt.scatter(X_pca[:, 10], X_pca[:, 11], c=y, cmap='viridis')
     plt.legend(handles=plot.legend_elements()[0], labels=set(y))
     plt.xlabel('Principal Component 0')
     plt.ylabel('Principal Component 1')
     plt.title('PCA Visualization')
     plt.show()
```



```
Number of components to keep 95% variance: 12
```



[ ]:
```
X_pca.shape
```

[ ]:
```
(540, 12)
```

[ ]:
```
y.shape
```

[ ]:
```
(540,)
```

[ ]:
```
# Merge X_pca and y into a new DataFrame rock1_df
rock_pca_df = pd.DataFrame(X_pca, columns=[f'PC{i}' for i in range(X_pca.
  ↪shape[1])])
rock_pca_df['Category'] = y
```

Q3- Splitting the data in testing , validation and training sets correctly

[ ]:
```
train,test = train_test_split(rock_pca_df, test_size=0.2,␣
  ↪stratify=rock_pca_df["Category"], random_state=42)
```

[ ]:
```
train["Category"].value_counts()/len(train)
```

```
[ ]: 2    0.333333
     1    0.333333
     3    0.333333
     Name: Category, dtype: float64
```

```
[ ]: test["Category"].value_counts()/len(test)
```

```
[ ]: 2    0.333333
     1    0.333333
     3    0.333333
     Name: Category, dtype: float64
```

Q3- Verification- The data is split into training and testing sets, with 20% reserved for testing. The 'stratify' parameter is used to ensure that both the training and testing sets maintain the same proportion of each class, which is crucial for maintaining a representative sample when dealing with imbalanced data or classification problems. During grid search CV the training set is split in partly and is assigned as validation set.

Special treatment: Encoding target variable to easily handle processing of data

```
[ ]: x_train,x_test =train.drop(columns=["Category"]),test.drop(columns=["Category"])
     y_train,y_test = train["Category"],test["Category"]
     encode = LabelEncoder()
     y_train = encode.fit_transform(y_train)
     y_test = encode.fit_transform(y_test)
```

```
[ ]: x_train.shape
```

```
[ ]: (432, 12)
```

```
[ ]: #one hot encoding for nominal and label encoder for ordinal
     from sklearn.pipeline import Pipeline
     from sklearn.preprocessing import StandardScaler
     from sklearn.compose import ColumnTransformer
     from sklearn.preprocessing import OneHotEncoder,OrdinalEncoder,LabelEncoder
     from sklearn.model_selection import train_test_split, GridSearchCV
```

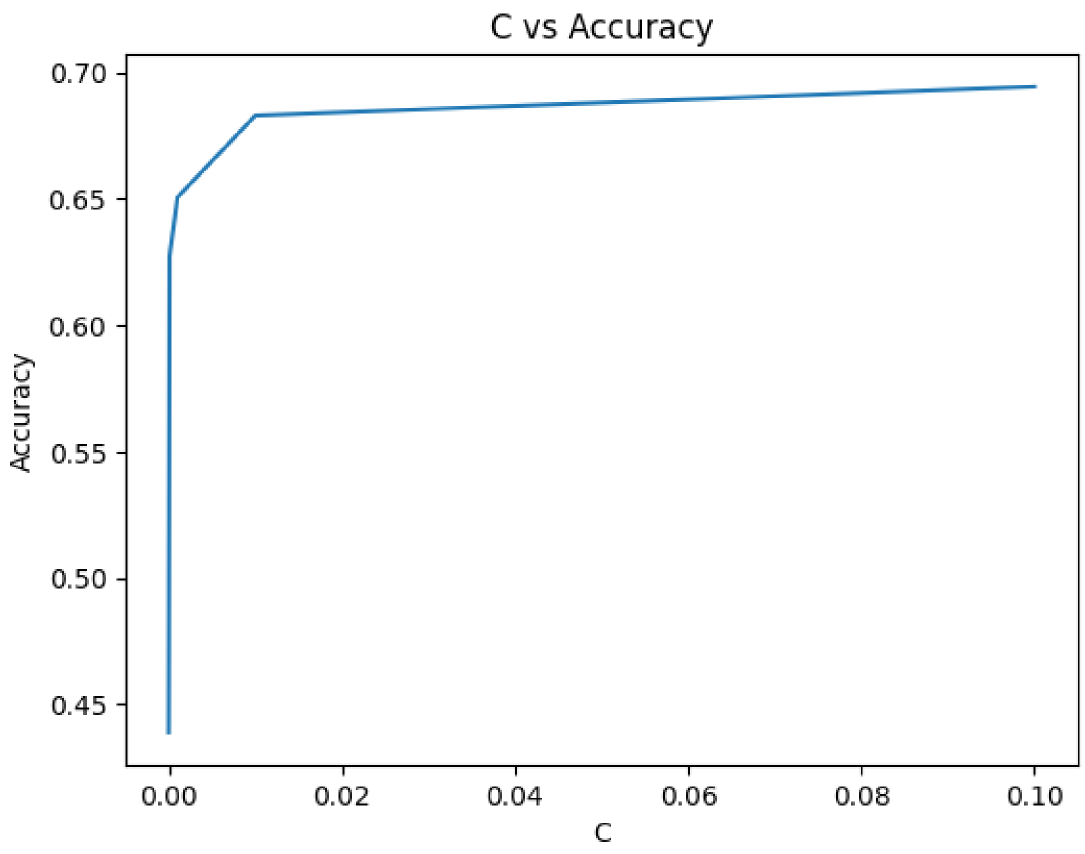
```
[ ]: # Specify the list of numeric features (e.g., PCs)
     numeric_features = [f'PC{i}' for i in range(1, 11 + 1)]  # Replace n with the␣
      ↪number of PCs you've retained

     # Create a StandardScaler and transform your PCA data
     scaler = StandardScaler()
     x_train[numeric_features] = scaler.fit_transform(x_train[numeric_features])
     x_test[numeric_features] = scaler.transform(x_test[numeric_features])
```

```
[ ]: x_train.shape
[ ]: (432, 12)
```

Question 4 a Multinomial Logistic Regression Q4a differerent hyparameters- c, solver , iter

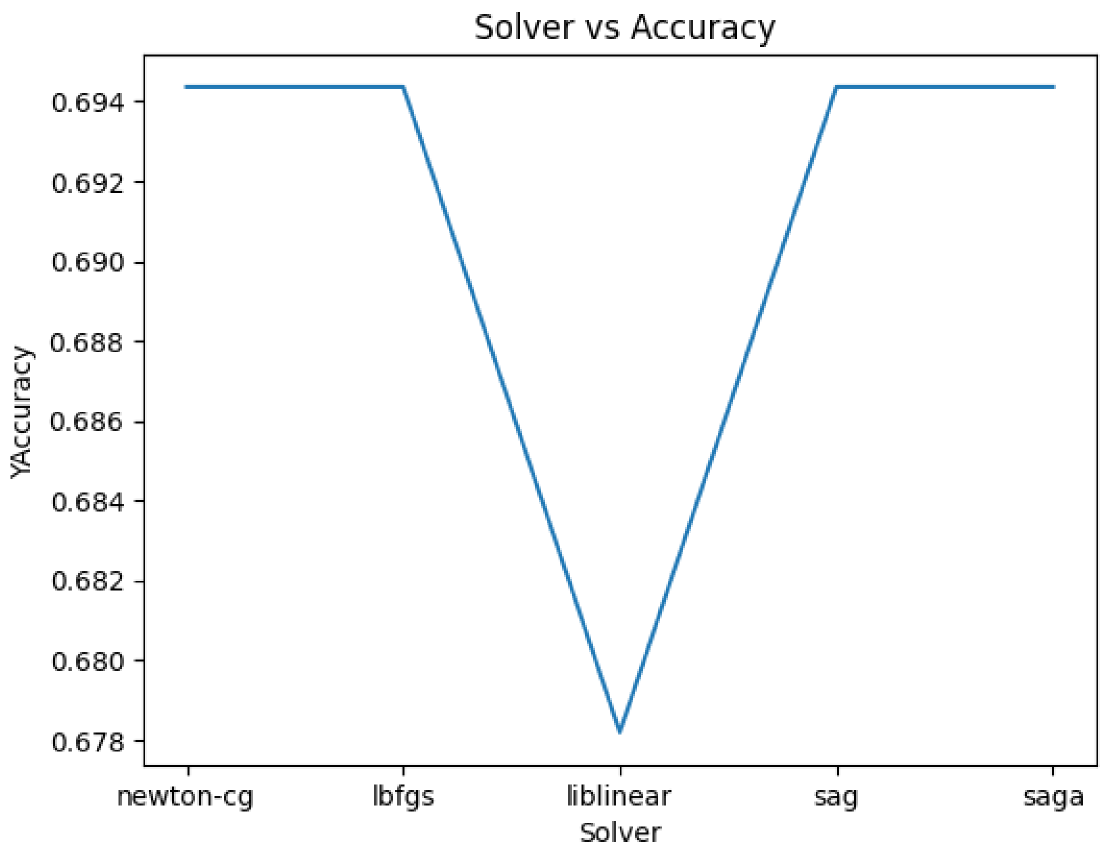
```
[ ]: from sklearn.linear_model import LogisticRegression
     from sklearn.model_selection import GridSearchCV
     import seaborn as sns
     import matplotlib.pyplot as plt
     softmax_reg = LogisticRegression()

     #automatic stratified split happens here
     C = [0.000001, 0.00001, 0.0001,0.001,0.01, 0.1]
     param_grid = {
         'C': C}
     grid_search = GridSearchCV(softmax_reg, param_grid=param_grid,
                                cv=5, n_jobs=-1, scoring="accuracy")
     grid_search.fit(x_train, y_train)
     results = grid_search.cv_results_
     accuracy_scores = results["mean_test_score"]
```

```
[ ]: sns.lineplot(x=C, y=accuracy_scores)
     # Add labels and a title
     plt.xlabel('C')
     plt.ylabel('Accuracy')
     plt.title('C vs Accuracy')

     # Show the plot
     plt.show()
```

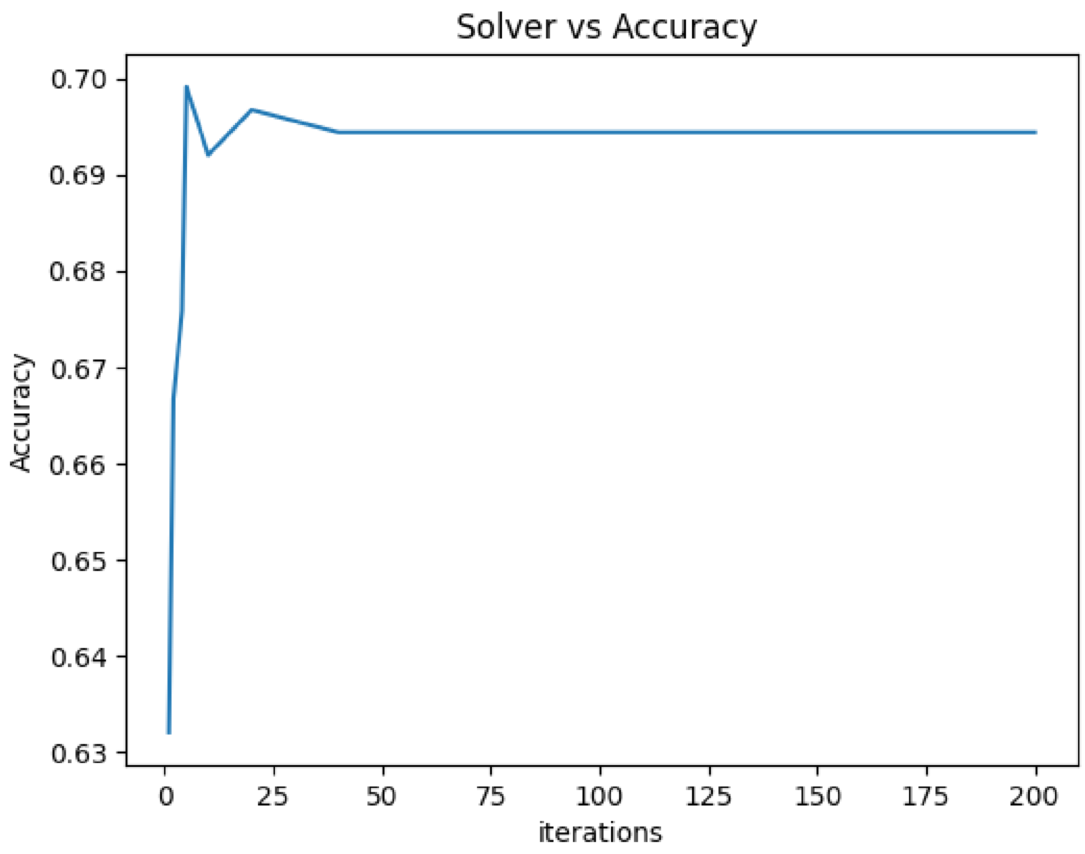


One can see that, when C is small[regularization parameter), the accuracy is less. Lesses the C, stronger the regularization. But as we increase C, the accuracy also increases, decreasing the amount of regularization

```
[ ]: solver = ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']
     param_grid = {
         'solver': solver}
     grid_search = GridSearchCV(softmax_reg, param_grid=param_grid,
                                cv=5, n_jobs=-1, scoring="accuracy")
     grid_search.fit(x_train, y_train)
     results = grid_search.cv_results_
     accuracy_scores = results["mean_test_score"]
     sns.lineplot(x=solver, y=accuracy_scores)
     # Add labels and a title
     plt.xlabel('Solver')
     plt.ylabel('YAccuracy')
     plt.title(' Solver vs Accuracy')

     # Show the plot
     plt.show()
```



[ ]:
```
max_iter= [1,2,4,5,10,20,40,50,100,200]
param_grid = {
    'max_iter': max_iter}
grid_search = GridSearchCV(softmax_reg, param_grid=param_grid,
                           cv=5, n_jobs=-1, scoring="accuracy")
grid_search.fit(x_train, y_train)
results = grid_search.cv_results_
accuracy_scores = results["mean_test_score"]
sns.lineplot(x=max_iter, y=accuracy_scores)
# Add labels and a title
plt.xlabel('iterations')
plt.ylabel('Accuracy')
plt.title(' Solver vs Accuracy')

# Show the plot
plt.show()
```



increasing the max_iter increases the accuracy scores. But after a particular range it becomes constant. Logistic regression algorithms are trained using optimization Algorithms such as gradient descent where the model converges to the local minima after certain number of iterations. hence providing with ebough iteration is important

Q4a- Best hyperparameters

```
[ ]: #find best model
param_grid = {
    'C': [0.0001, 0.001, 0.01,0.1, 1.0, 10,20],
    'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'],
    'max_iter': [10,20,40,50,100,200, 300, 500]
}
grid_search = GridSearchCV(softmax_reg, param_grid=param_grid,
                           cv=5, n_jobs=-1,␣
 ↪scoring="accuracy",return_train_score=True)
grid_search.fit(x_train, y_train)
print("tuned hpyerparameters :(best parameters) ",grid_search.best_params_)
print("accuracy :",grid_search.best_score_)
```

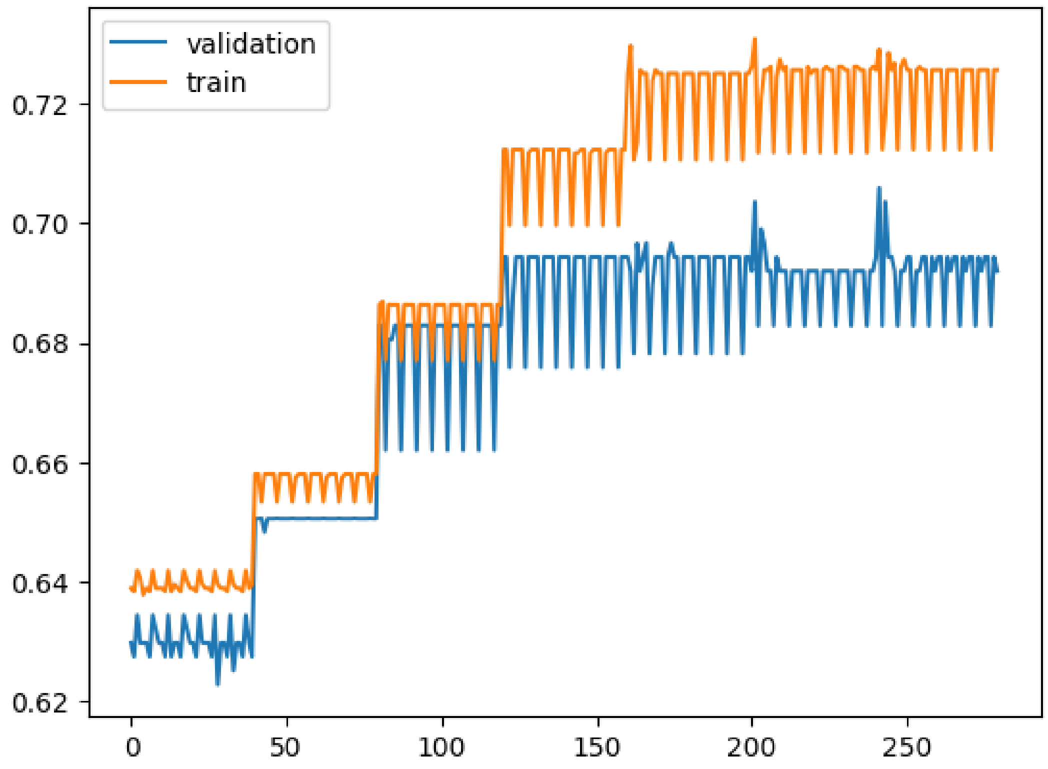
```
tuned hpyerparameters :(best parameters)  {'C': 20, 'max_iter': 10, 'solver':
```

```
'lbfgs'}
accuracy : 0.7059609730018711
```

[ ]:
```
best_parameters = {'C': 20, 'max_iter': 10, 'solver': 'lbfgs'}
```

Q4a- Training vs validation results

[ ]:
```
validation_scores = grid_search.cv_results_['mean_test_score']
train_scores = grid_search.cv_results_['mean_train_score']
plt.plot(validation_scores, label='validation')
plt.plot(train_scores, label='train')
plt.legend(loc='best')
plt.show()
```



Q4a Performance

[ ]:
```
best_log_model = grid_search.best_estimator_
y_pred = best_log_model.predict(x_test)
from sklearn.metrics import precision_score, recall_score, f1_score

# Compute precision, recall, and F1 score
precision = precision_score(y_test, y_pred, average='weighted')  # You can␣
  ↪choose 'micro', 'macro', or 'weighted'
```

```
recall = recall_score(y_test, y_pred, average='weighted')  # You can choose␣
↪'micro', 'macro', or 'weighted'
f1 = f1_score(y_test, y_pred, average='weighted')  # You can choose 'micro',␣
↪'macro', or 'weighted'
# Print the results
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
```

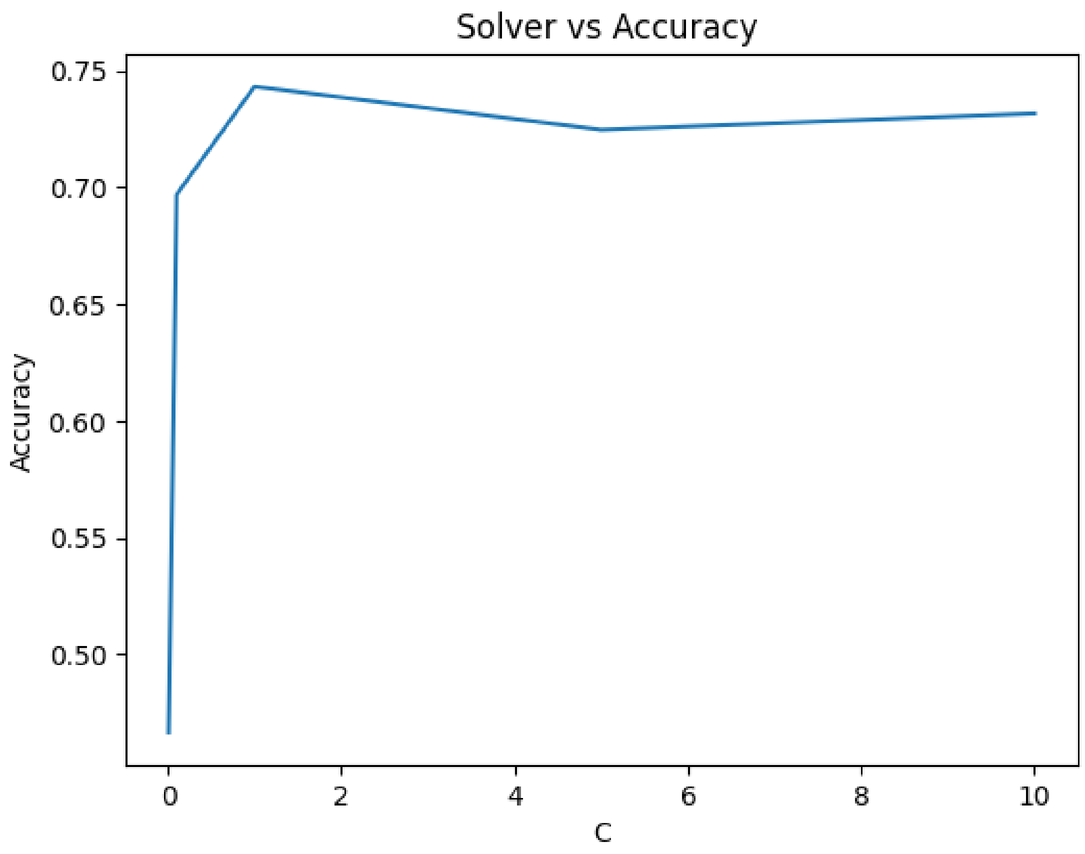
```
Precision: 0.7026315789473685
Recall: 0.6944444444444444
F1 Score: 0.6957196430880641
```

Q4 b SVM Model implementation

```
[ ]: #SVMs
from sklearn.svm import SVC
svm = SVC(probability=True)
param_grid = {
    'C': [0.01,0.1, 1,10],
    'kernel': ['linear', 'rbf', 'poly'],
    'gamma': [0.001, 0.01, 0.1, 1],
    'degree': [2, 3, 4],
}
```

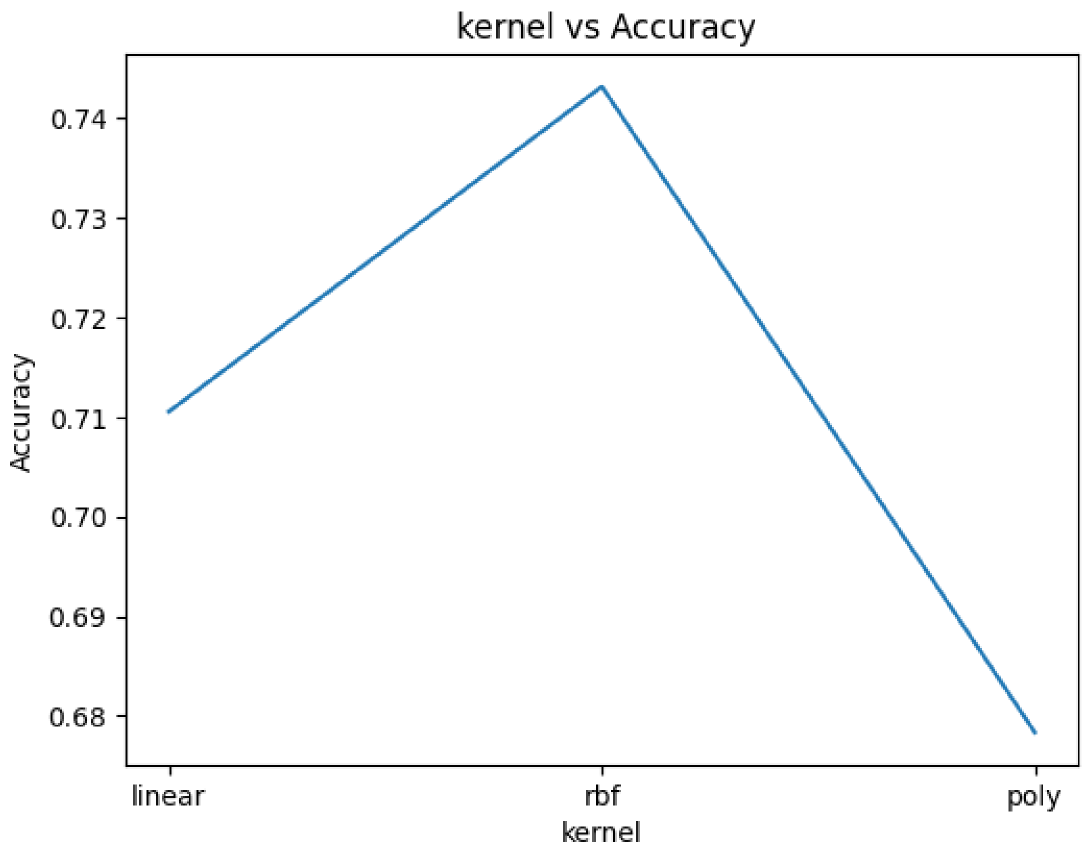
Different hyperparameters

```
[ ]: C=[0.01,0.1,5, 1.0,10.0]
param_grid = {
    'C': C}
grid_search = GridSearchCV(svm, param_grid=param_grid,
                           cv=5, n_jobs=-1, scoring="accuracy")
grid_search.fit(x_train, y_train)
results = grid_search.cv_results_
accuracy_scores = results["mean_test_score"]
sns.lineplot(x=C, y=accuracy_scores)
# Add labels and a title
plt.xlabel('C')
plt.ylabel('Accuracy')
plt.title(' Solver vs Accuracy')
# Show the plot
plt.show()
```



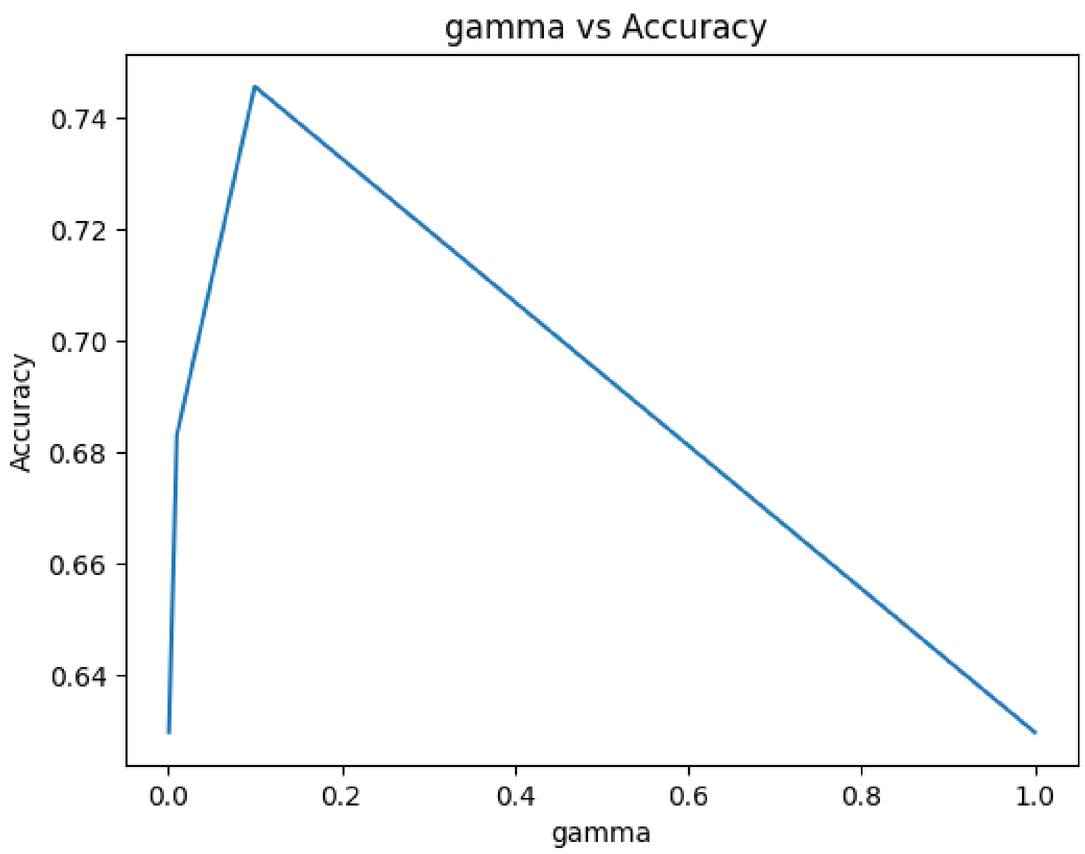
One can see that, when C is small[regularization parameter), the accuracy is less. Lesses the C, stronger the regularization. But as we increase C, the accuracy also increases, decreasing the amount of regularization

```
[ ]: kernel=['linear', 'rbf', 'poly']
     param_grid = {
         'kernel': kernel}
     grid_search = GridSearchCV(svm, param_grid=param_grid,
                                cv=5, n_jobs=-1, scoring="accuracy")
     grid_search.fit(x_train, y_train)
     results = grid_search.cv_results_
     accuracy_scores = results["mean_test_score"]
     sns.lineplot(x=kernel, y=accuracy_scores)
     # Add labels and a title
     plt.xlabel('kernel')
     plt.ylabel('Accuracy')
     plt.title(' kernel vs Accuracy')
     # Show the plot
     plt.show()
```



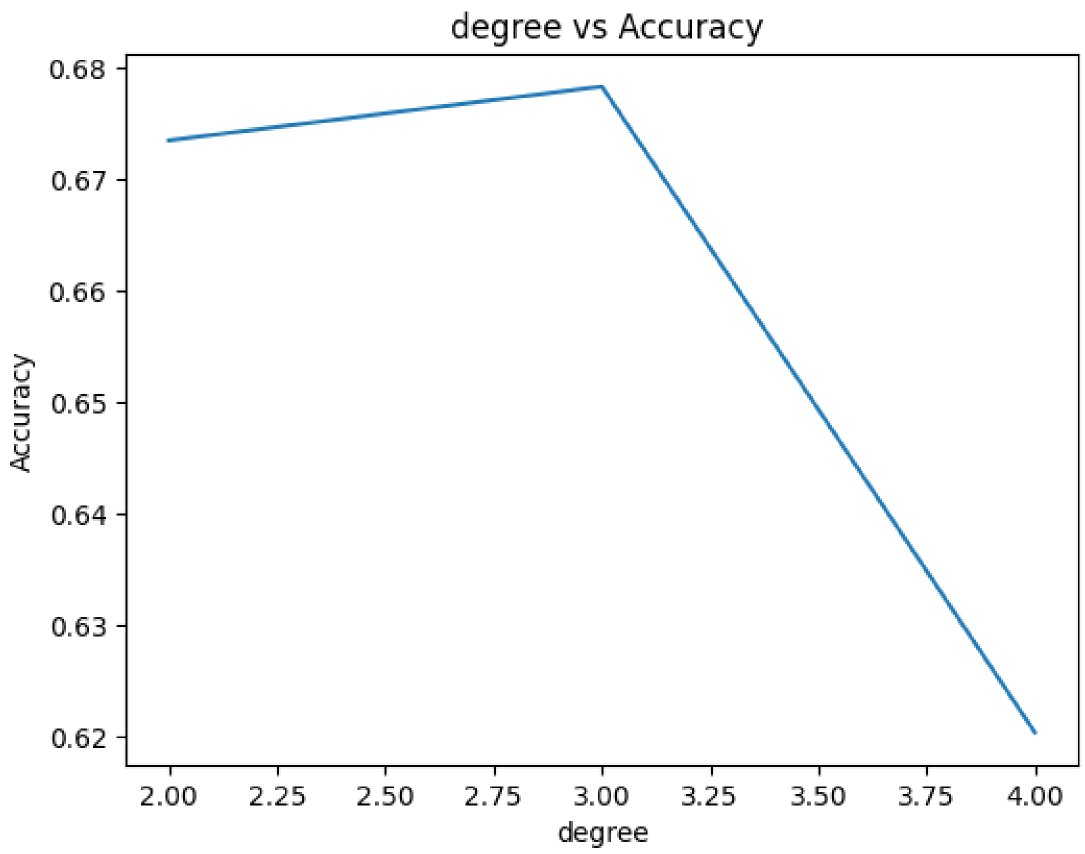
Ine can see that rbf kernel has higher accuracy compared to other kernels.Because the use case in hand is complex and may have decision boundaries that are complex, rbf kernel with its ability to create non linear transformation has performed better.

```
[ ]: gamma= [0.001, 0.01, 0.1, 1]
     param_grid = {
         'gamma': gamma}
     grid_search = GridSearchCV(svm, param_grid=param_grid,
                                cv=5, n_jobs=-1, scoring="accuracy")
     grid_search.fit(x_train, y_train)
     results = grid_search.cv_results_
     accuracy_scores = results["mean_test_score"]
     sns.lineplot(x=gamma, y=accuracy_scores)
     # Add labels and a title
     plt.xlabel('gamma')
     plt.ylabel('Accuracy')
     plt.title(' gamma vs Accuracy')
     # Show the plot
     plt.show()
```



gamma parameter defines how smooth and generalized athe decsion bounday has to be. Higher the gamma, closely it fits to the training samples leading to overfitting which in turn decrease accuracy

[ ]:
```
degree= [2, 3, 4]
param_grid = {
    'degree': degree}
grid_search = GridSearchCV(SVC(kernel="poly"), param_grid=param_grid,
                           cv=5, n_jobs=-1, scoring="accuracy")
grid_search.fit(x_train, y_train)
results = grid_search.cv_results_
accuracy_scores = results["mean_test_score"]
sns.lineplot(x=degree, y=accuracy_scores)
# Add labels and a title
plt.xlabel('degree')
plt.ylabel('Accuracy')
plt.title(' degree vs Accuracy')
# Show the plot
plt.show()
```



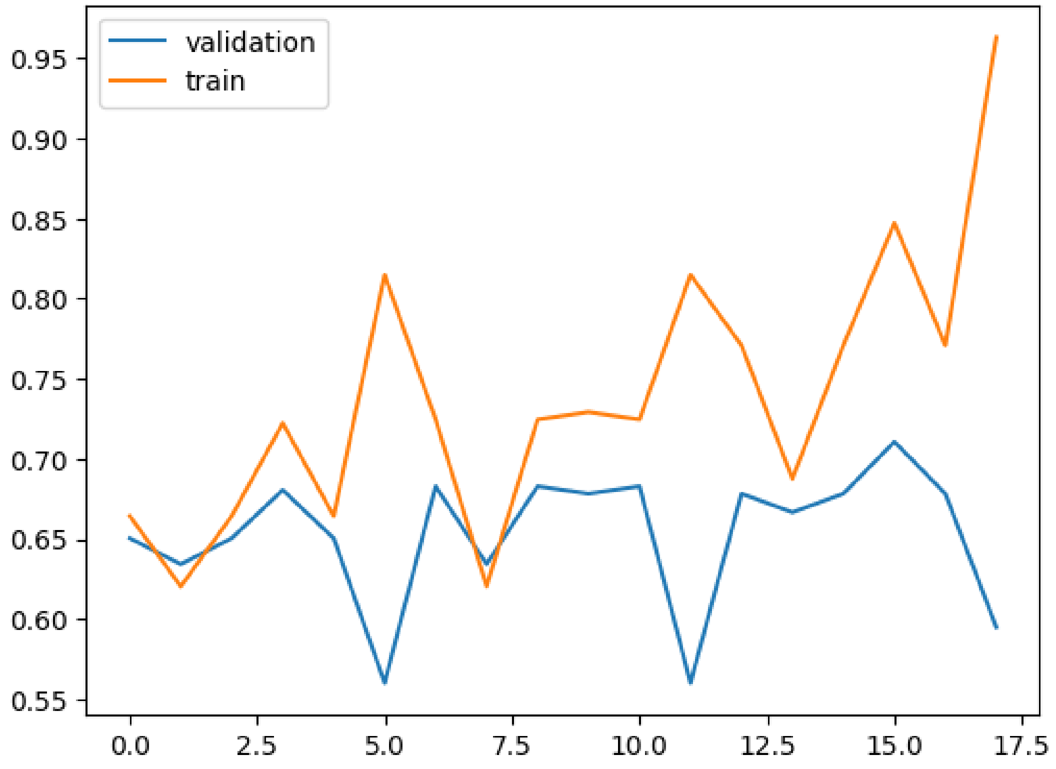
a lower polynomial degree is used when the variables are linearly separable.Increasing the number of degress leads to model being overft, which inturn reduces the testing accuracy.

Best hyperparamter/model

```
[ ]: #best model
svc = SVC(probability=True)
param_grid = {
    'C': [0.01,0.1, 1],
    'kernel': ['linear', 'rbf'],
    'gamma': [0.01, 0.1, 1]
}
grid_search = GridSearchCV(svc, param_grid=param_grid,
                           cv=2, n_jobs=-1,␣
 ↪scoring="accuracy",return_train_score=True)
grid_search.fit(x_train, y_train)
print("tuned hpyerparameters :(best parameters) ",grid_search.best_params_)
print("accuracy :",grid_search.best_score_)
validation_scores = grid_search.cv_results_['mean_test_score']
train_scores = grid_search.cv_results_['mean_train_score']
```

```
plt.plot(validation_scores, label='validation')
plt.plot(train_scores, label='train')
plt.legend(loc='best')
plt.show()
```

```
tuned hpyerparameters :(best parameters)  {'C': 1, 'gamma': 0.1, 'kernel':
'rbf'}
accuracy : 0.7106481481481481
```



Performance testing

```
[ ]: from sklearn.metrics import classification_report, confusion_matrix
     best_svm_model = grid_search.best_estimator_
     y_pred = best_svm_model.predict(x_test)
     # Compute precision, recall, and F1 score
     precision = precision_score(y_test, y_pred, average='macro')
     recall = recall_score(y_test, y_pred, average='macro')
     f1 = f1_score(y_test, y_pred, average='macro')
     # Print the results
     print("Precision:", precision)
     print("Recall:", recall)
     print("F1 Score:", f1)
print(classification_report(y_test, y_pred))
```

```
Precision: 0.7207861086893347
Recall: 0.7129629629629629
F1 Score: 0.7147266551166304
              precision    recall  f1-score   support

           0       0.84      0.72      0.78        36
           1       0.65      0.67      0.66        36
           2       0.68      0.75      0.71        36

    accuracy                           0.71       108
   macro avg       0.72      0.71      0.71       108
weighted avg       0.72      0.71      0.71       108
```

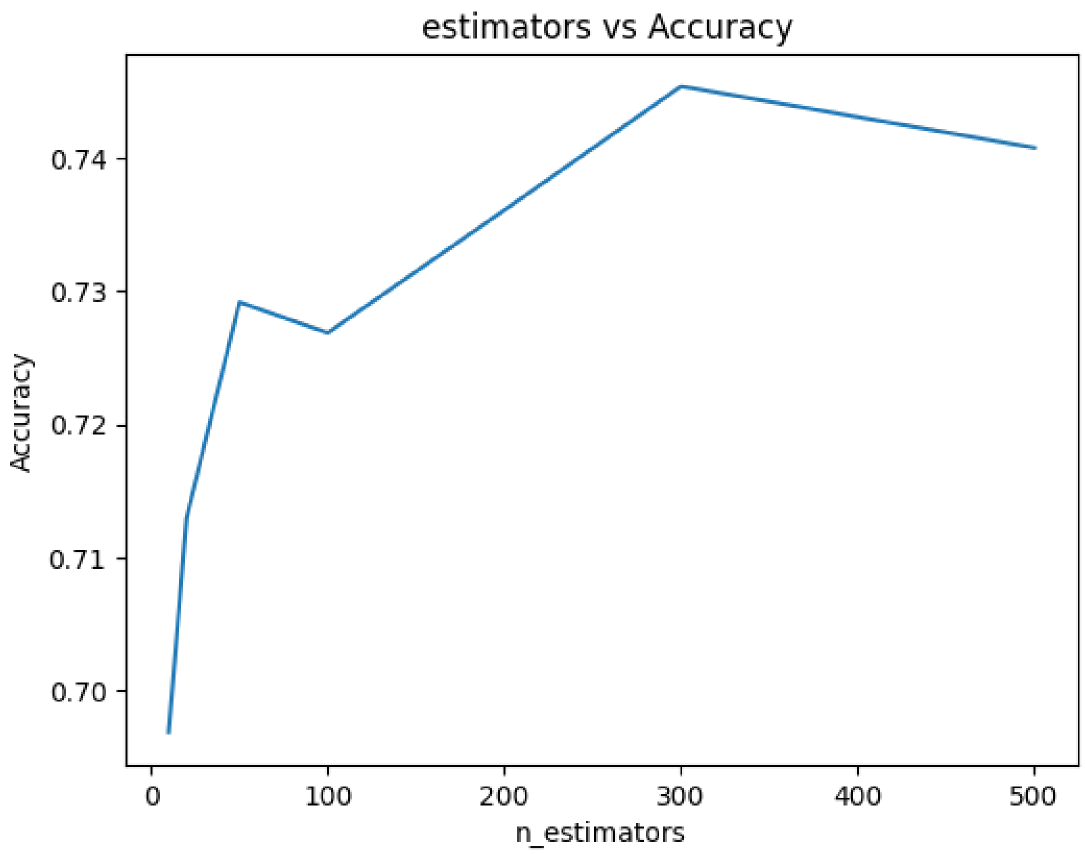
Q4c Random forrest

```
[ ]: #random forest
     from sklearn.ensemble import RandomForestClassifier
     param_grid = {
         'n_estimators': [50, 100, 200, 300, 500],  # Number of trees in the forest
         'max_depth': [None, 10, 20, 30],  # Maximum depth of each tree
         'min_samples_split': [2, 5, 10],  # Minimum number of samples required to␣
       ↪split an internal node
         'min_samples_leaf': [1, 2, 4],  # Minimum number of samples required to be␣
       ↪at a leaf node
     }
```

```
[ ]: rf_clf = RandomForestClassifier()
```

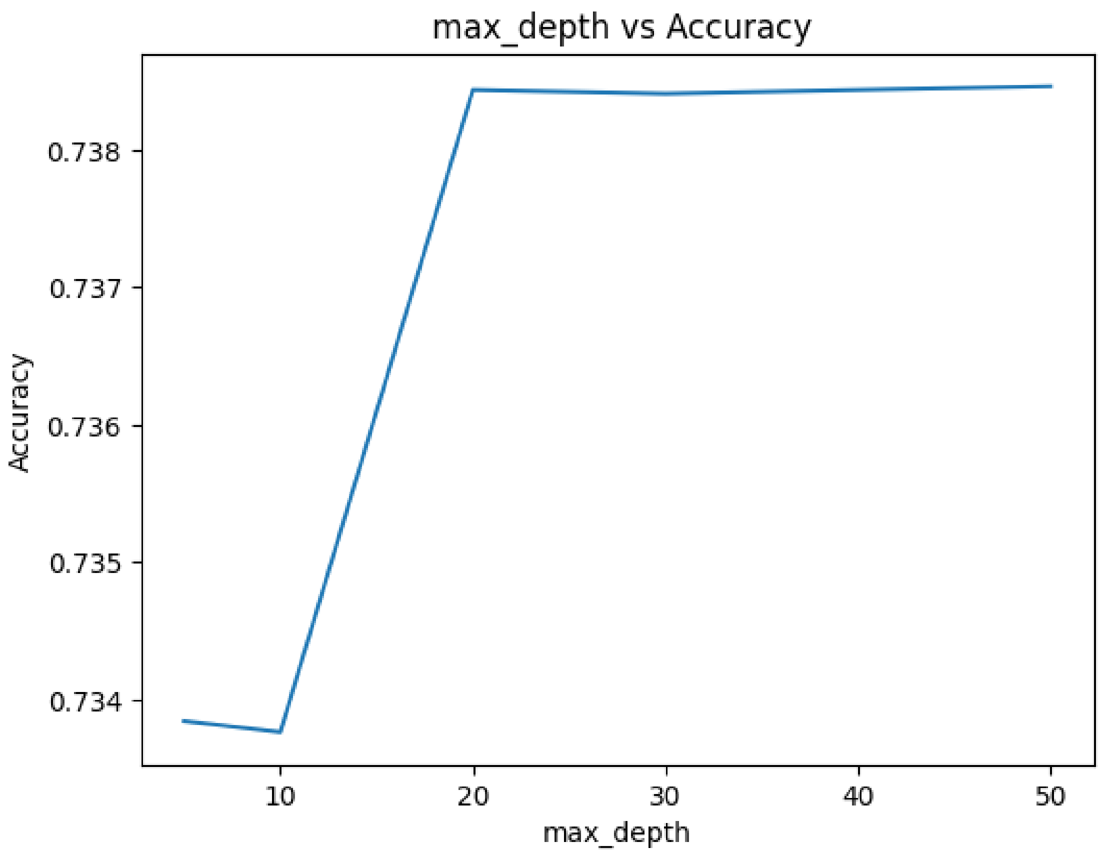
Different hyperparameters

```
[ ]: n_estimators=[10,20,50, 100, 200, 300, 500]
     param_grid = {
         'n_estimators': n_estimators}
     grid_search = GridSearchCV(rf_clf, param_grid=param_grid,
                                cv=5, n_jobs=-1, scoring="accuracy")
     grid_search.fit(x_train, y_train)
     results = grid_search.cv_results_
     accuracy_scores = results["mean_test_score"]
     sns.lineplot(x=n_estimators, y=accuracy_scores)
     # Add labels and a title
     plt.xlabel('n_estimators')
     plt.ylabel('Accuracy')
     plt.title(' estimators vs Accuracy')
     # Show the plot
     plt.show()
```



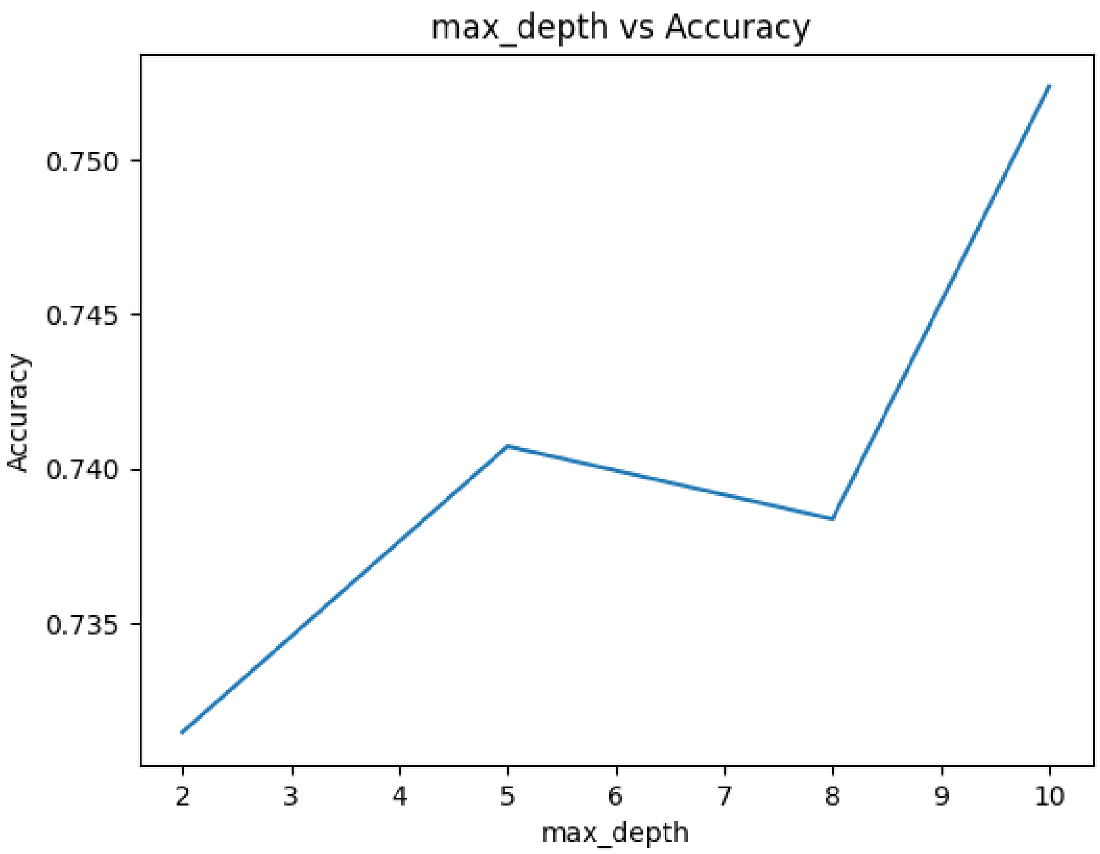
n_estimators defines the number of decision trees that needs to be created. higher the decsion tree, the probability of overfitting increases, and lower it is, the model might be underfit. In this scenario, one can see that the accuracy starts to decrease when estimators increase from 300-500, which means the model is overfitting

[ ]:
```
max_depth= [0, 5, 10, 20, 30,50]
param_grid = {
    'max_depth': max_depth}
grid_search = GridSearchCV(rf_clf, param_grid=param_grid,
                           cv=5, n_jobs=-1, scoring="accuracy")
grid_search.fit(x_train, y_train)
results = grid_search.cv_results_
accuracy_scores = results["mean_test_score"]
sns.lineplot(x=max_depth, y=accuracy_scores)
# Add labels and a title
plt.xlabel('max_depth')
plt.ylabel('Accuracy')
plt.title(' max_depth vs Accuracy')
# Show the plot
plt.show()
```



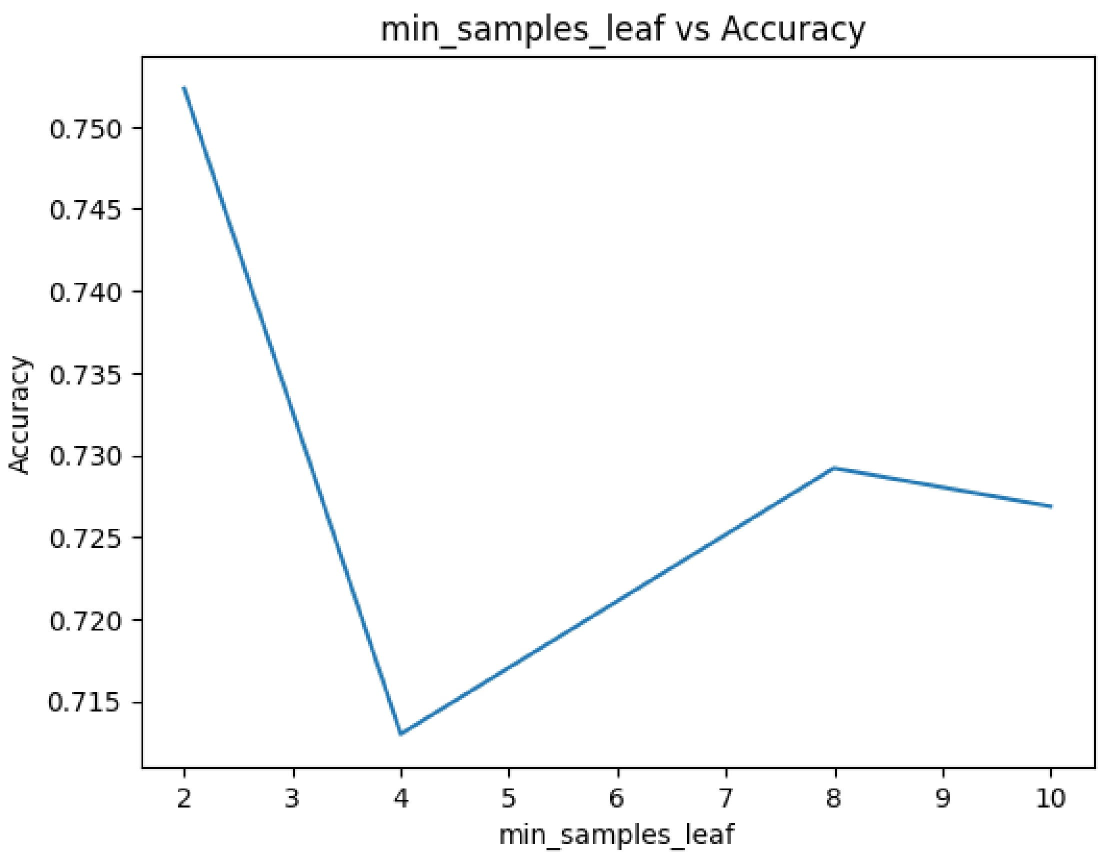
Lesser max_depth results in trees that are simpler and less complex. But as you increase the max_depth, the accuracy increases and starts decreasing after reaching the highest accuracy as the model will start to overfit

[ ]:
```
min_samples_split= [1,2, 5, 8,10]
param_grid = {
    'min_samples_split': min_samples_split}
grid_search = GridSearchCV(rf_clf, param_grid=param_grid,
                           cv=5, n_jobs=-1, scoring="accuracy")
grid_search.fit(x_train, y_train)
results = grid_search.cv_results_
accuracy_scores = results["mean_test_score"]
sns.lineplot(x=min_samples_split, y=accuracy_scores)
# Add labels and a title
plt.xlabel('max_depth')
plt.ylabel('Accuracy')
plt.title(' max_depth vs Accuracy')
# Show the plot
plt.show()
```



A small “min samples split” means it allows the nodes to split even when there are less samples at node, which may lead to overfitting

```
[ ]: min_samples_leaf= [2,4,8,10]  # Minimum number of samples required to be at a␣
      ↪leaf node
     param_grid = {
         'min_samples_leaf': min_samples_leaf}
     grid_search = GridSearchCV(rf_clf, param_grid=param_grid,
                                cv=5, n_jobs=-1, scoring="accuracy")
     grid_search.fit(x_train, y_train)
     results = grid_search.cv_results_
     accuracy_scores = results["mean_test_score"]
     sns.lineplot(x=min_samples_leaf, y=accuracy_scores)
     # Add labels and a title
     plt.xlabel('min_samples_leaf')
     plt.ylabel('Accuracy')
     plt.title(' min_samples_leaf vs Accuracy')
     # Show the plot
     plt.show()
```



increasing the min_samples_leaf makes the model underfit the data as the trees becomes shallower and simpler, inturn reducing the overall accuracy.

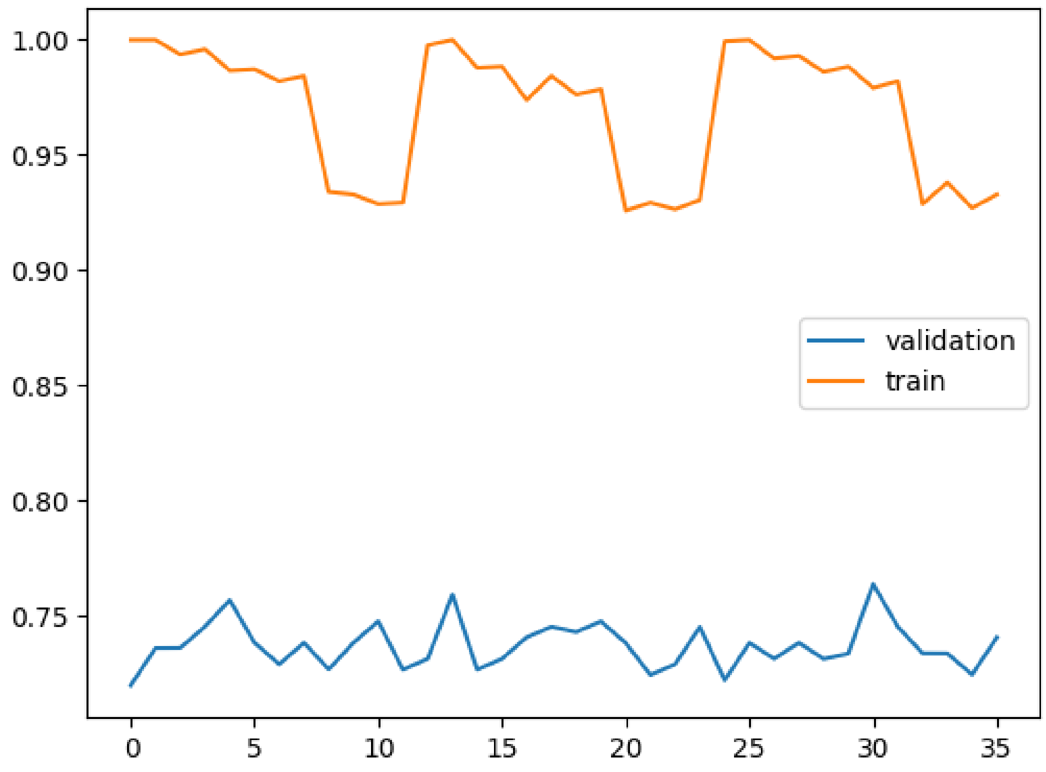
Best hyperparameter / model

```
[ ]: param_grid = {
         'n_estimators': [50, 100],  # Number of trees in the forest
         'max_depth': [None, 10, 20],  # Maximum depth of each tree
         'min_samples_split': [2, 5],  # Minimum number of samples required to split␣
      ↪an internal node
         'min_samples_leaf': [1, 2, 4],  # Minimum number of samples required to be␣
      ↪at a leaf node
     }
```

Testing and validation

```
[ ]: grid_search = GridSearchCV(rf_clf, param_grid=param_grid,
                                cv=5, n_jobs=-1,␣
      ↪scoring="accuracy",return_train_score=True)
     grid_search.fit(x_train, y_train)
     print("tuned hpyerparameters :(best parameters) ",grid_search.best_params_)
     print("accuracy :",grid_search.best_score_)

     validation_scores = grid_search.cv_results_['mean_test_score']
     train_scores = grid_search.cv_results_['mean_train_score']
     plt.plot(validation_scores, label='validation')
     plt.plot(train_scores, label='train')
     plt.legend(loc='best')
     plt.show()
```

```
tuned hpyerparameters :(best parameters)  {'max_depth': 20, 'min_samples_leaf':
2, 'min_samples_split': 5, 'n_estimators': 50}
accuracy : 0.7638866613205025
```



Performance

```
[ ]: best_rf_clf_model = grid_search.best_estimator_
y_pred = best_rf_clf_model.predict(x_test)
# Compute precision, recall, and F1 score
precision = precision_score(y_test, y_pred, average='macro')
recall = recall_score(y_test, y_pred, average='macro')
f1 = f1_score(y_test, y_pred, average='macro')
# Print the results
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
print(classification_report(y_test, y_pred))
```

```
Precision: 0.746253465003465
Recall: 0.7407407407407408
F1 Score: 0.7421488047273703
              precision    recall  f1-score   support

           0       0.84      0.75      0.79        36
           1       0.69      0.75      0.72        36
           2       0.70      0.72      0.71        36

    accuracy                           0.74       108
   macro avg       0.75      0.74      0.74       108
weighted avg       0.75      0.74      0.74       108
```

[ ]:
```
rock_cat_df = rock_pca_df.copy()
```

Q5 - Ensemble classifier

[ ]:
```
#Ensemble methods
#voting classifer
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
ensemble_classifier = VotingClassifier(estimators=[
    ("log", best_log_model),
    ("rf", best_rf_clf_model),
    ("svm", best_svm_model)
], voting="hard")
#ensemble_classifier = VotingClassifier(estimators =␣
 ↪[("log",best_log_model),("rf",best_rf_clf_model)],voting="hard")
ensemble_classifier.fit(x_train,y_train)
ensemble_predictions = ensemble_classifier.predict(x_test)
# Evaluate the ensemble's performance
ensemble_accuracy = accuracy_score(y_test, ensemble_predictions)
print("Ensemble Accuracy:", ensemble_accuracy)
for name, clf in ensemble_classifier.named_estimators_.items():
  print(name, "=", clf.score(x_test, y_test))
```

```
Ensemble Accuracy: 0.75
log = 0.05555555555555555
rf = 0.05555555555555555
svm = 0.07407407407407407
```

[ ]:
```
#Ensemble methods
#voting classifer
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
ensemble_classifier = VotingClassifier(estimators=[
    ("log", best_log_model),
    ("rf", best_rf_clf_model),
    ("svm", best_svm_model)
], voting="soft")
#ensemble_classifier = VotingClassifier(estimators =␣
 ↪[("log",best_log_model),("rf",best_rf_clf_model)],voting="hard")
ensemble_classifier.fit(x_train,y_train)
ensemble_predictions = ensemble_classifier.predict(x_test)
# Evaluate the ensemble's performance
ensemble_accuracy = accuracy_score(y_test, ensemble_predictions)
print("Ensemble Accuracy:", ensemble_accuracy)
for name, clf in ensemble_classifier.named_estimators_.items():
  print(name, "=", clf.score(x_test, y_test))
```

```
Ensemble Accuracy: 0.75
log = 0.05555555555555555
rf = 0.05555555555555555
svm = 0.07407407407407407
```

Ensemble accuracy greater than other classifiers

[ ]:
```
from sklearn.ensemble import VotingClassifier,AdaBoostClassifier
```

[ ]:
```
adaBoostClassifier = AdaBoostClassifier(estimator=ensemble_classifier,␣
 ↪n_estimators=100, algorithm='SAMME')
adaBoostClassifier.fit(x_train, y_train)
```

[ ]:
```
AdaBoostClassifier(algorithm='SAMME',
                   estimator=VotingClassifier(estimators=[('log',
LogisticRegression(C=20,
max_iter=10)),
                                                          ('rf',
RandomForestClassifier(max_depth=20,
  min_samples_leaf=2,
  min_samples_split=5,
  n_estimators=50)),
                                                          ('svm',
                                                           SVC(C=1, gamma=0.1,
probability=True))]),
                   n_estimators=100)
```

Test set accuracy

```
[ ]: ensemble_predictions = adaBoostClassifier.predict(x_test)
     # Evaluate the ensemble's performance
     ensemble_accuracy = accuracy_score(y_test, ensemble_predictions)
     print("Ensemble Accuracy:", ensemble_accuracy)
```

```
     Ensemble Accuracy: 0.7037037037037037
```

```
[ ]: ''' voting_clf.voting = "soft"
     voting_clf.named_estimators["svc"].probability = True
     voting_clf.fit(X_train, y_train)
     voting_clf.score(X_test, y_test) '''
```

```
[ ]: ' voting_clf.voting = "soft"\nvoting_clf.named_estimators["svc"].probability =
     True\nvoting_clf.fit(X_train, y_train)\nvoting_clf.score(X_test, y_test) '
```

```
[ ]: #bagging
     from sklearn.ensemble import BaggingClassifier
     bag_clf = BaggingClassifier(DecisionTreeClassifier(),␣
      ↪n_estimators=500,max_samples=100, n_jobs=-1, random_state=42)
     bag_clf.fit(x_train, y_train)
```

```
[ ]: BaggingClassifier(estimator=DecisionTreeClassifier(), max_samples=100,
                       n_estimators=500, n_jobs=-1, random_state=42)
```

```
[ ]: #gradient boosting
     from sklearn.ensemble import GradientBoostingClassifier
     gb_classifier = GradientBoostingClassifier(n_estimators=500, learning_rate=0.1,␣
      ↪max_depth=3,n_iter_no_change=20 )
     gb_classifier.fit(x_train, y_train)
     gb_predictions = gb_classifier.predict(x_test)
     gb_accuracy = accuracy_score(y_test, gb_predictions)
     print("Gradient Boosting Classifier Accuracy:", gb_accuracy)
```

```
     Gradient Boosting Classifier Accuracy: 0.7129629629629629
```

```
[ ]: from sklearn.ensemble import StackingClassifier
     stacking_clf = StackingClassifier(estimators=[('lr', best_log_model),('rf',␣
      ↪best_rf_clf_model),("svm", best_svm_model)],
                                   final_estimator=best_log_model,
                                   cv=10)
     stacking_clf.fit(x_train, y_train)
```

```
[ ]: StackingClassifier(cv=10,
                        estimators=[('lr', LogisticRegression(C=20, max_iter=10)),
                                    ('rf',
                                     RandomForestClassifier(max_depth=20,
                                                            min_samples_leaf=2,
                                                min_samples_split=5,
                                                n_estimators=50)),
                                ('svm', SVC(C=1, gamma=0.1, probability=True))],
                       final_estimator=LogisticRegression(C=20, max_iter=10))
```

```
[ ]: stacking_pred = stacking_clf.predict(x_test)
     stacking_accuracy = accuracy_score(y_test, stacking_pred)
     print("Gradient Boosting Classifier Accuracy:", stacking_accuracy)
```

```
Gradient Boosting Classifier Accuracy: 0.7314814814814815
```

Conclusion Ensemble learning results indicate that logistic regression performs the most effectively after employing AdaBoost, when compared to logistic regression, random forest, and support vector classifier (SVC).

4c) Feature Importance continued

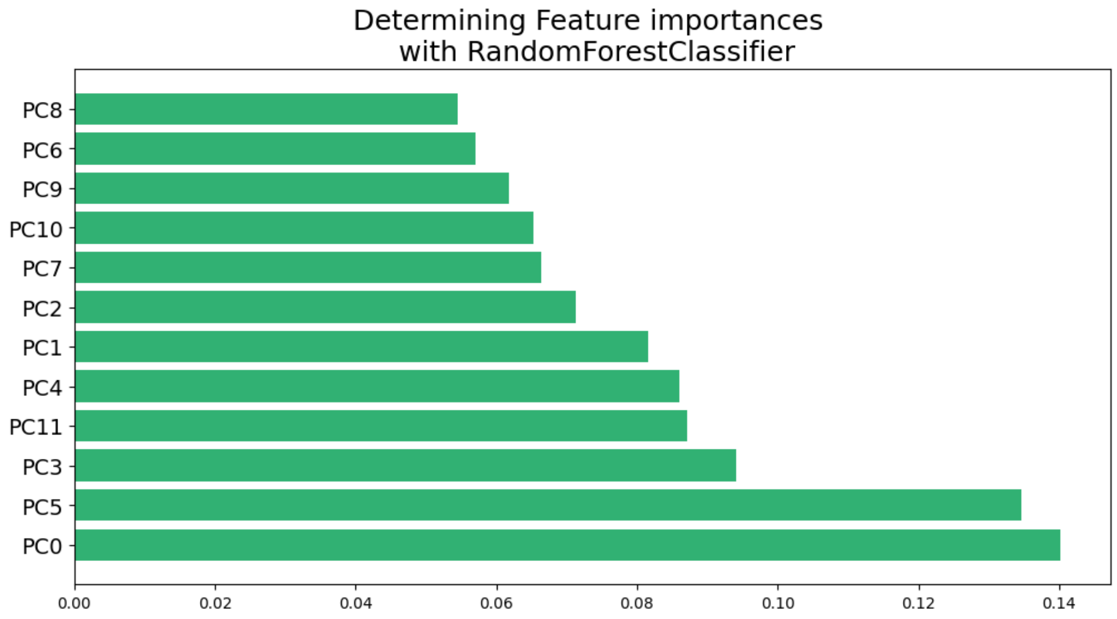
```
[ ]: # List of columns you want to convert
     columns_to_convert = rock_cat_df.columns[1:]  # Replace this with the actual␣
      ↪list of columns you want to convert

     for column in columns_to_convert:
         if rock_cat_df[column].dtype == 'object':
             rock_cat_df[column] = rock_cat_df[column].astype('category').cat.codes
```

```
[ ]: x = rock_pca_df.drop(columns=["Category"])
     y = rock_pca_df["Category"]
     x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,stratify=y)
     rf_clf = RandomForestClassifier(max_depth= None, min_samples_leaf= 1,␣
      ↪min_samples_split= 5, n_estimators= 100)
     rf_clf.fit(x_train,y_train)
     y_pred = rf_clf.predict(x_test)
     precision = precision_score(y_test, y_pred, average='macro')
     recall = recall_score(y_test, y_pred, average='macro')
     f1 = f1_score(y_test, y_pred, average='macro')
     # Print the results
     print("Precision:", precision)
     print("Recall:", recall)
     print("F1 Score:", f1)
     print(classification_report(y_test, y_pred))
```

```
Precision: 0.7700929152148664
Recall: 0.7685185185185185
F1 Score: 0.7673348468708867
              precision    recall  f1-score   support

           1       0.83      0.81      0.82        36
           2       0.73      0.83      0.78        36
           3       0.75      0.67      0.71        36

    accuracy                           0.77       108
   macro avg       0.77      0.77      0.77       108
weighted avg       0.77      0.77      0.77       108
```

[ ]:
```
importances = rf_clf.feature_importances_
feature_names = x_test.columns
indices = np.argsort(importances)[::-1]

# Print the feature ranking
print("Feature ranking:")

for f in range(x_train.shape[1]):
    print("%d. feature %d (%f)" % (f + 1, indices[f], importances[indices[f]]))

# Plot the feature importances of the forest
def feature_importance_graph(indices, importances, feature_names):
    plt.figure(figsize=(12,6))
    plt.title("Determining Feature importances \n with RandomForestClassifier",␣
 ↪fontsize=18)
    plt.barh(range(len(indices)), importances[indices], color='#31B173', ␣
 ↪align="center")
    plt.yticks(range(len(indices)), feature_names[indices],␣
 ↪rotation='horizontal',fontsize=14)
    plt.ylim([-1, len(indices)])

feature_importance_graph(indices, importances, feature_names)
plt.show()
```

```
Feature ranking:
1. feature 0 (0.140257)
2. feature 5 (0.134602)
3. feature 3 (0.094038)
4. feature 11 (0.087138)
5. feature 4 (0.086000)
6. feature 1 (0.081579)
7. feature 2 (0.071271)
8. feature 7 (0.066463)
9. feature 10 (0.065270)
10. feature 9 (0.061821)
11. feature 6 (0.057113)
12. feature 8 (0.054448)
```


Determining Feature importances
with RandomForestClassifier
PC8
PC6
PC9
PC10
PC7
PC2
PC1
PC4
PC11
PC3
PC5
PC0
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14