```
import requests
from io import StringIO
import pandas as pd
from scipy.io import arff
```

```
from scipy.io import arff
import pandas as pd
import requests
from io import StringIO

# URL of the dataset in ARFF format
url = 'http://promise.site.uottawa.ca/SERepository/datasets/jm1.arff'

# Download the dataset
response = requests.get(url)

# Load the dataset from the response content
data = arff.loadarff(StringIO(response.content.decode('utf-8')))
df = pd.DataFrame(data[0])

# Print the first few rows of the DataFrame
print(df.head())
```

```
     loc  v(g)  ev(g)  iv(g)      n        v     l      d       i         e  \
0    1.1   1.4    1.4    1.4    1.3     1.30  1.30   1.30    1.30      1.30
1    1.0   1.0    1.0    1.0    1.0     1.00  1.00   1.00    1.00      1.00
2   72.0   7.0    1.0    6.0  198.0  1134.13  0.05  20.31   55.85  23029.10
3  190.0   3.0    1.0    3.0  600.0  4348.76  0.06  17.06  254.87  74202.67
4   37.0   4.0    1.0    4.0  126.0   599.12  0.06  17.19   34.86  10297.30

   ...  lOCode  lOComment  lOBlank  locCodeAndComment  uniq_Op  uniq_Opnd  \
0  ...     2.0        2.0      2.0                2.0      1.2        1.2
1  ...     1.0        1.0      1.0                1.0      1.0        1.0
2  ...    51.0       10.0      8.0                1.0     17.0       36.0
3  ...   129.0       29.0     28.0                2.0     17.0      135.0
4  ...    28.0        1.0      6.0                0.0     11.0       16.0

   total_Op  total_Opnd  branchCount   defects
0       1.2         1.2          1.4  b'false'
1       1.0         1.0          1.0   b'true'
2     112.0        86.0         13.0   b'true'
3     329.0       271.0          5.0   b'true'
4      76.0        50.0          7.0   b'true'

[5 rows x 22 columns]
```

```
from sklearn.preprocessing import StandardScaler, LabelEncoder

# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Encode the 'defects' column
df['defects'] = label_encoder.fit_transform(df['defects'])

# Separate the 'defects' column from the rest of the data
defects_column = df['defects']

# Drop the 'defects' column from the DataFrame
df = df.drop(columns=['defects'])

# Initialize StandardScaler
scaler = StandardScaler()

# Fit scaler to your data and transform it
scaled_data = scaler.fit_transform(df)

# Concatenate the scaled features with the 'defects' column
scaled_df = pd.DataFrame(scaled_data, columns=df.columns)
scaled_df['defects'] = defects_column

# Print the first few rows of the scaled DataFrame
print(scaled_df.head())
```

```
        loc      v(g)     ev(g)     iv(g)         n         v         l  \
0 -0.534225 -0.380102 -0.295508 -0.285373 -0.453283 -0.346848  7.255076
1 -0.535530 -0.410826 -0.354578 -0.329250 -0.454485 -0.347003  5.386279
2  0.391486  0.050035 -0.354578  0.219208  0.335124  0.237456 -0.531578
3  1.932161 -0.257206 -0.354578 -0.109867  1.946407  1.895536 -0.469285
4 -0.065494 -0.180396 -0.354578 -0.000175  0.046536 -0.038498 -0.469285

          d         i         e  ...    lOCode  lOComment   lOBlank  \
```

```
0 -0.688290 -0.817612 -0.084805  ... -0.406860  -0.081873 -0.263405
1 -0.704325 -0.826329 -0.084806  ... -0.423636  -0.192883 -0.363730
2  0.327797  0.767373 -0.031788  ...  0.415171   0.806207  0.338540
3  0.154084  6.550025  0.086029  ...  1.723710   2.915398  2.345027
4  0.161032  0.157495 -0.061101  ...  0.029320  -0.192883  0.137892

   locCodeAndComment   uniq_Op  uniq_Opnd  total_Op  total_Opnd  branchCount  \
0           0.853939 -0.993310  -0.583195 -0.441634   -0.450326    -0.437779
1           0.329798 -1.013221  -0.590695 -0.442954   -0.452319    -0.455481
2           0.329798  0.579644   0.721806  0.289686    0.394739     0.075573
3           0.853939  0.579644   4.434307  1.721964    2.238338    -0.278463
4          -0.194344 -0.017680  -0.028195  0.052073    0.035985    -0.189954

   defects
0        0
1        1
2        1
3        1
4        1

[5 rows x 22 columns]
```

```
print(df.shape)  # Check the dimensions of the DataFrame
print(df.head())  # Display the first few rows of the DataFrame
```

```
(10885, 21)
     loc  v(g)  ev(g)  iv(g)      n        v     l      d       i         e  \
0    1.1   1.4    1.4    1.4    1.3     1.30  1.30   1.30    1.30      1.30
1    1.0   1.0    1.0    1.0    1.0     1.00  1.00   1.00    1.00      1.00
2   72.0   7.0    1.0    6.0  198.0  1134.13  0.05  20.31   55.85  23029.10
3  190.0   3.0    1.0    3.0  600.0  4348.76  0.06  17.06  254.87  74202.67
4   37.0   4.0    1.0    4.0  126.0   599.12  0.06  17.19   34.86  10297.30

   ...        t  lOCode  lOComment  lOBlank  locCodeAndComment  uniq_Op  \
0  ...     1.30     2.0        2.0      2.0                2.0      1.2
1  ...     1.00     1.0        1.0      1.0                1.0      1.0
2  ...  1279.39    51.0       10.0      8.0                1.0     17.0
3  ...  4122.37   129.0       29.0     28.0                2.0     17.0
4  ...   572.07    28.0        1.0      6.0                0.0     11.0

   uniq_Opnd  total_Op  total_Opnd  branchCount
0        1.2       1.2         1.2          1.4
1        1.0       1.0         1.0          1.0
2       36.0     112.0        86.0         13.0
3      135.0     329.0       271.0          5.0
4       16.0      76.0        50.0          7.0

[5 rows x 21 columns]
```

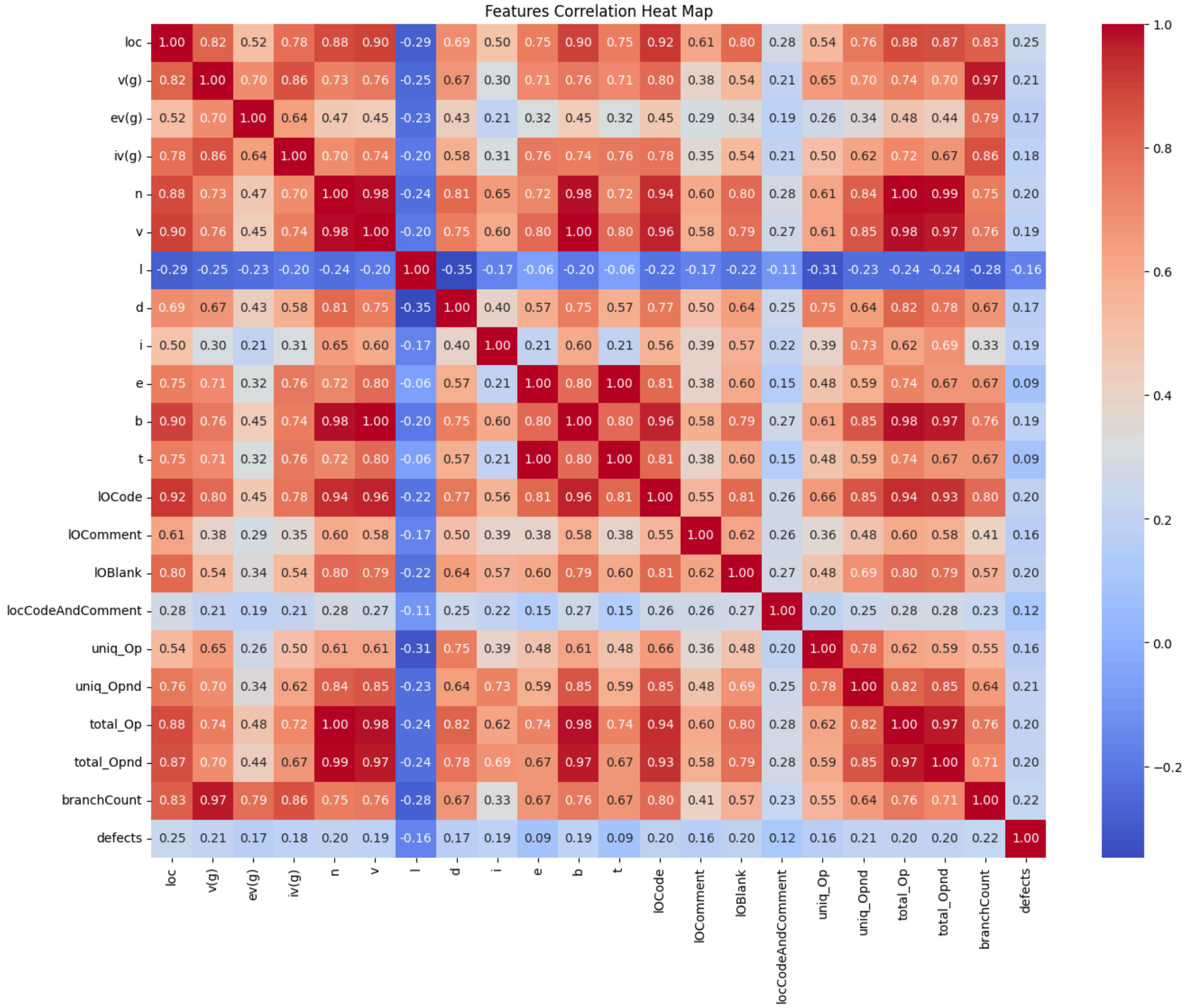
```
# Remove rows with null values
df.dropna(inplace=True)
```

```
# Check for NaN values in each column
nan_counts = df.isna().sum()

# Display columns with NaN values, if any
columns_with_nan = nan_counts[nan_counts > 0].index.tolist()
if columns_with_nan:
    print("Columns with NaN values:", columns_with_nan)
else:
    print("No NaN values remaining in the DataFrame")
```

```
No NaN values remaining in the DataFrame
```

```
# Plotting the features correlation heat map
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(16, 12))
correlation_matrix = scaled_df.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Features Correlation Heat Map')
plt.show()
```


Features Correlation Heat Map
loc
v(g)
ev(g)
iv(g)
n
v
l
d
i
e
b
t
lOCode
lOComment
lOBlank
locCodeAndComment
uniq_Op
uniq_Opnd
total_Op
total_Opnd
branchCount
defects
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

```
from sklearn.cluster import KMeans
from sklearn.impute import SimpleImputer
import matplotlib.pyplot as plt
# Drop the 'defects' column for clustering
clustering_data = scaled_df.drop(columns=['defects'])
# Instantiate the imputer
imputer = SimpleImputer(strategy='mean')  # You can choose another strategy if needed

# Impute missing values
clustering_data_imputed = imputer.fit_transform(clustering_data)

# Determine the optimal number of clusters using the elbow method
inertia = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(clustering_data_imputed)
    inertia.append(kmeans.inertia_)

# Plot the elbow curve
plt.plot(range(1, 11), inertia, marker='o')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal K')
plt.show()

# From the elbow curve, choose the optimal number of clusters
optimal_k = 2  # Example: Based on the plot, choose the optimal number of clusters

# Apply K-means clustering with the optimal number of clusters
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
clusters = kmeans.fit_predict(clustering_data_imputed)

# Add cluster labels to the DataFrame
scaled_df['cluster'] = clusters

# Print the first few rows of the DataFrame with cluster labels
print(scaled_df.head())
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
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  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
```
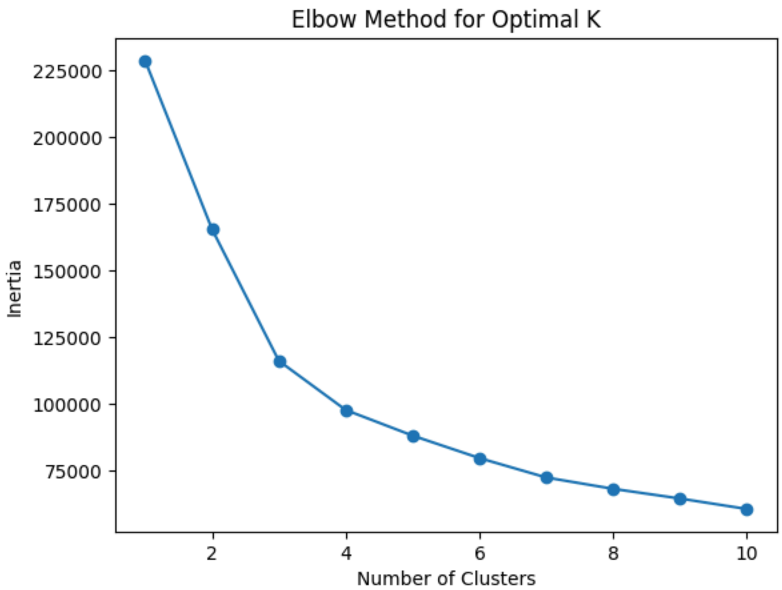




```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
        loc      v(g)     ev(g)     iv(g)         n         v         l  \
0 -0.534225 -0.380102 -0.295508 -0.285373 -0.453283 -0.346848  7.255076
1 -0.535530 -0.410826 -0.354578 -0.329250 -0.454485 -0.347003  5.386279
2  0.391486  0.050035 -0.354578  0.219208  0.335124  0.237456 -0.531578
3  1.932161 -0.257206 -0.354578 -0.109867  1.946407  1.895536 -0.469285
4 -0.065494 -0.180396 -0.354578 -0.000175  0.046536 -0.038498 -0.469285

          d         i         e  ...  lOComment   lOBlank  locCodeAndComment  \
0 -0.688290 -0.817612 -0.084805  ...  -0.081873 -0.263405           0.853939
1 -0.704325 -0.826329 -0.084806  ...  -0.192883 -0.363730           0.329798
```

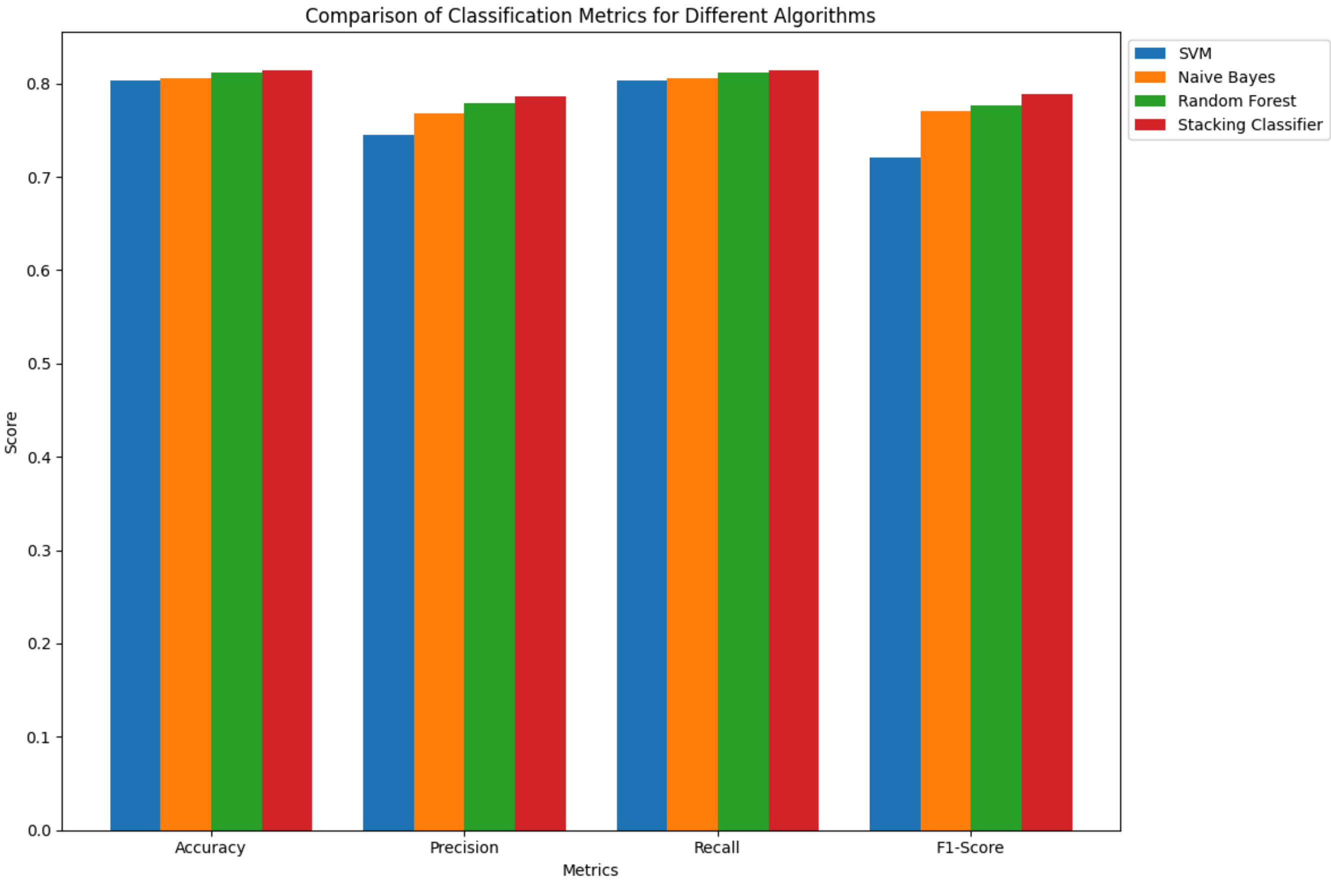
```
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier, StackingClassifier
from sklearn.metrics import accuracy_score

# Split the data into training and testing sets
X = scaled_df.drop(columns=['defects', 'cluster'])  # Features
y = scaled_df['defects']  # Target variable
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)

# Initialize classifiers
svm_classifier = SVC(kernel='linear', random_state=42)
nb_classifier = GaussianNB()
rf_classifier = RandomForestClassifier(n_estimators=1000, random_state=42)

# Initialize stacking classifier
estimators = [('svm', svm_classifier), ('nb', nb_classifier), ('rf', rf_classifier)]
stacking_classifier = StackingClassifier(estimators=estimators, final_estimator=nb_classifier)

from sklearn.impute import SimpleImputer

# Instantiate the imputer
imputer = SimpleImputer(strategy='mean')  # You can choose another strategy if needed

# Impute missing values in X_train
X_train_imputed = imputer.fit_transform(X_train)

# Impute missing values in X_test
X_test_imputed = imputer.transform(X_test)

# Train the classifiers with imputed data
svm_classifier.fit(X_train_imputed, y_train)
nb_classifier.fit(X_train_imputed, y_train)
rf_classifier.fit(X_train_imputed, y_train)
stacking_classifier.fit(X_train_imputed, y_train)

# Predictions
svm_pred = svm_classifier.predict(X_test_imputed)
nb_pred = nb_classifier.predict(X_test_imputed)
rf_pred = rf_classifier.predict(X_test_imputed)
stacking_pred = stacking_classifier.predict(X_test_imputed)

# Evaluate accuracy
svm_accuracy = accuracy_score(y_test, svm_pred)
nb_accuracy = accuracy_score(y_test, nb_pred)
rf_accuracy = accuracy_score(y_test, rf_pred)
stacking_accuracy = accuracy_score(y_test, stacking_pred)

# Print accuracies
print("SVM Accuracy:", svm_accuracy)
print("Naive Bayes Accuracy:", nb_accuracy)
print("Random Forest Accuracy:", rf_accuracy)
print("Stacking Classifier Accuracy:", stacking_accuracy)
```

```
SVM Accuracy: 0.8035068188143613
Naive Bayes Accuracy: 0.8054550514890064
Random Forest Accuracy: 0.812134706373504
Stacking Classifier Accuracy: 0.8143612580016699
```

```
from sklearn.metrics import classification_report

# Calculate metrics for SVM
svm_report = classification_report(y_test, svm_pred)
print("SVM Metrics:")
print(svm_report)

# Calculate metrics for Naive Bayes
nb_report = classification_report(y_test, nb_pred)
print("\nNaive Bayes Metrics:")
print(nb_report)

# Calculate metrics for Random Forest
rf_report = classification_report(y_test, rf_pred)
print("\nRandom Forest Metrics:")
print(rf_report)

# Calculate metrics for Stacking Classifier
stacking_report = classification_report(y_test, stacking_pred)
print("\nStacking Classifier Metrics:")
print(stacking_report)
```

```
SVM Metrics:
              precision    recall  f1-score   support

           0       0.81      1.00      0.89      2887
           1       0.50      0.01      0.03       706

    accuracy                           0.80      3593
   macro avg       0.65      0.51      0.46      3593
weighted avg       0.75      0.80      0.72      3593


Naive Bayes Metrics:
              precision    recall  f1-score   support

           0       0.83      0.95      0.89      2887
           1       0.51      0.21      0.29       706

    accuracy                           0.81      3593
   macro avg       0.67      0.58      0.59      3593
weighted avg       0.77      0.81      0.77      3593


Random Forest Metrics:
              precision    recall  f1-score   support

           0       0.83      0.96      0.89      2887
           1       0.56      0.22      0.31       706

    accuracy                           0.81      3593
   macro avg       0.69      0.59      0.60      3593
weighted avg       0.78      0.81      0.78      3593


Stacking Classifier Metrics:
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      2887
           1       0.55      0.28      0.37       706

    accuracy                           0.81      3593
   macro avg       0.70      0.61      0.63      3593
weighted avg       0.79      0.81      0.79      3593
```

```
import matplotlib.pyplot as plt

# Extracting metrics for SVM
svm_metrics = classification_report(y_test, svm_pred, output_dict=True)
svm_accuracy = svm_metrics['accuracy']
svm_precision = svm_metrics['weighted avg']['precision']
svm_recall = svm_metrics['weighted avg']['recall']
svm_f1_score = svm_metrics['weighted avg']['f1-score']

# Extracting metrics for Naive Bayes
nb_metrics = classification_report(y_test, nb_pred, output_dict=True)
nb_accuracy = nb_metrics['accuracy']
nb_precision = nb_metrics['weighted avg']['precision']
nb_recall = nb_metrics['weighted avg']['recall']
nb_f1_score = nb_metrics['weighted avg']['f1-score']

# Extracting metrics for Random Forest
rf_metrics = classification_report(y_test, rf_pred, output_dict=True)
rf_accuracy = rf_metrics['accuracy']
rf_precision = rf_metrics['weighted avg']['precision']
rf_recall = rf_metrics['weighted avg']['recall']
rf_f1_score = rf_metrics['weighted avg']['f1-score']

# Extracting metrics for Stacking Classifier
stacking_metrics = classification_report(y_test, stacking_pred, output_dict=True)
stacking_accuracy = stacking_metrics['accuracy']
stacking_precision = stacking_metrics['weighted avg']['precision']
stacking_recall = stacking_metrics['weighted avg']['recall']
stacking_f1_score = stacking_metrics['weighted avg']['f1-score']

# Plotting
labels = ['Accuracy', 'Precision', 'Recall', 'F1-Score']
svm_values = [svm_accuracy, svm_precision, svm_recall, svm_f1_score]
nb_values = [nb_accuracy, nb_precision, nb_recall, nb_f1_score]
rf_values = [rf_accuracy, rf_precision, rf_recall, rf_f1_score]
stacking_values = [stacking_accuracy, stacking_precision, stacking_recall, stacking_f1_score]

x = range(len(labels))

plt.figure(figsize=(12, 8))  # Increase the figure size

plt.bar(x, svm_values, width=0.2, label='SVM', align='center')
plt.bar([i + 0.2 for i in x], nb_values, width=0.2, label='Naive Bayes', align='center')
plt.bar([i + 0.4 for i in x], rf_values, width=0.2, label='Random Forest', align='center')
plt.bar([i + 0.6 for i in x], stacking_values, width=0.2, label='Stacking Classifier', align='center')

plt.xlabel('Metrics')
plt.ylabel('Score')
plt.title('Comparison of Classification Metrics for Different Algorithms')
plt.xticks([i + 0.3 for i in x], labels)
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))  # Move legend outside the plot

plt.tight_layout()  # Adjust subplots to fit into figure area.
plt.show()
```




```
# prompt: i want to calculate MAE, RMSE, and MAPE, of applied algorithms

from sklearn.metrics import mean_absolute_error, mean_squared_error, mean_absolute_percentage_error

# Calculate mean absolute error (MAE)
svm_mae = mean_absolute_error(y_test, svm_pred)
nb_mae = mean_absolute_error(y_test, nb_pred)
rf_mae = mean_absolute_error(y_test, rf_pred)
stacking_mae = mean_absolute_error(y_test, stacking_pred)

# Calculate root mean squared error (RMSE)
svm_rmse = mean_squared_error(y_test, svm_pred, squared=False)
nb_rmse = mean_squared_error(y_test, nb_pred, squared=False)
rf_rmse = mean_squared_error(y_test, rf_pred, squared=False)
stacking_rmse = mean_squared_error(y_test, stacking_pred, squared=False)


# Print the calculated metrics
print("SVM MAE:", svm_mae)
print("Naive Bayes MAE:", nb_mae)
print("Random Forest MAE:", rf_mae)
print("Stacking Classifier MAE:", stacking_mae)

print("\nSVM RMSE:", svm_rmse)
print("Naive Bayes RMSE:", nb_rmse)
print("Random Forest RMSE:", rf_rmse)
print("Stacking Classifier RMSE:", stacking_rmse)
```

```
SVM MAE: 0.19649318118563874
Naive Bayes MAE: 0.1945449485109936
Random Forest MAE: 0.18786529362649595
Stacking Classifier MAE: 0.18563874199833008

SVM RMSE: 0.4432755138575091
Naive Bayes RMSE: 0.4410724980215765
Random Forest RMSE: 0.4334343013958355
```

```
Stacking Classifier RMSE: 0.4308581460275877
```

```
import matplotlib.pyplot as plt
import numpy as np

# Define the algorithms and their corresponding metrics
algorithms = ['SVM', 'Naive Bayes', 'Random Forest', 'Stacking Classifier']
```