NAVNEEL MONDAL **Reg No: 21BCE2654**

DATE: 21-09-2023

AI ML ASSIGNMENT-4

1. **Download the dataset:** winequality_red.csv is downloaded.

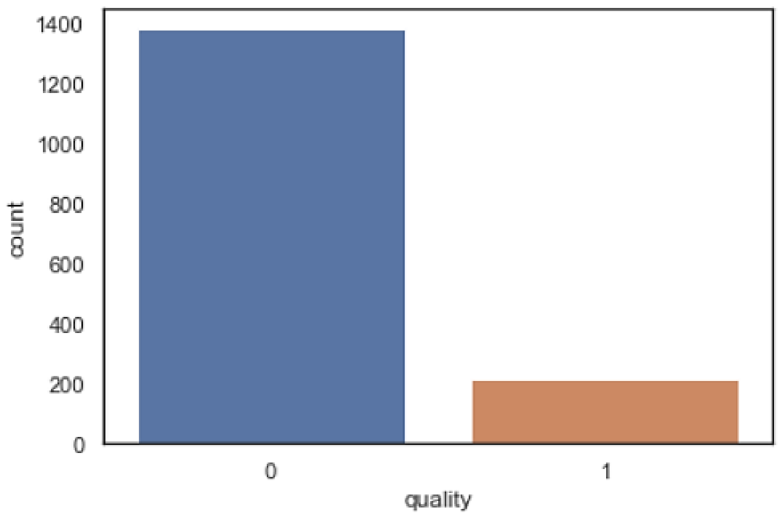
2. **Load The dataset:**

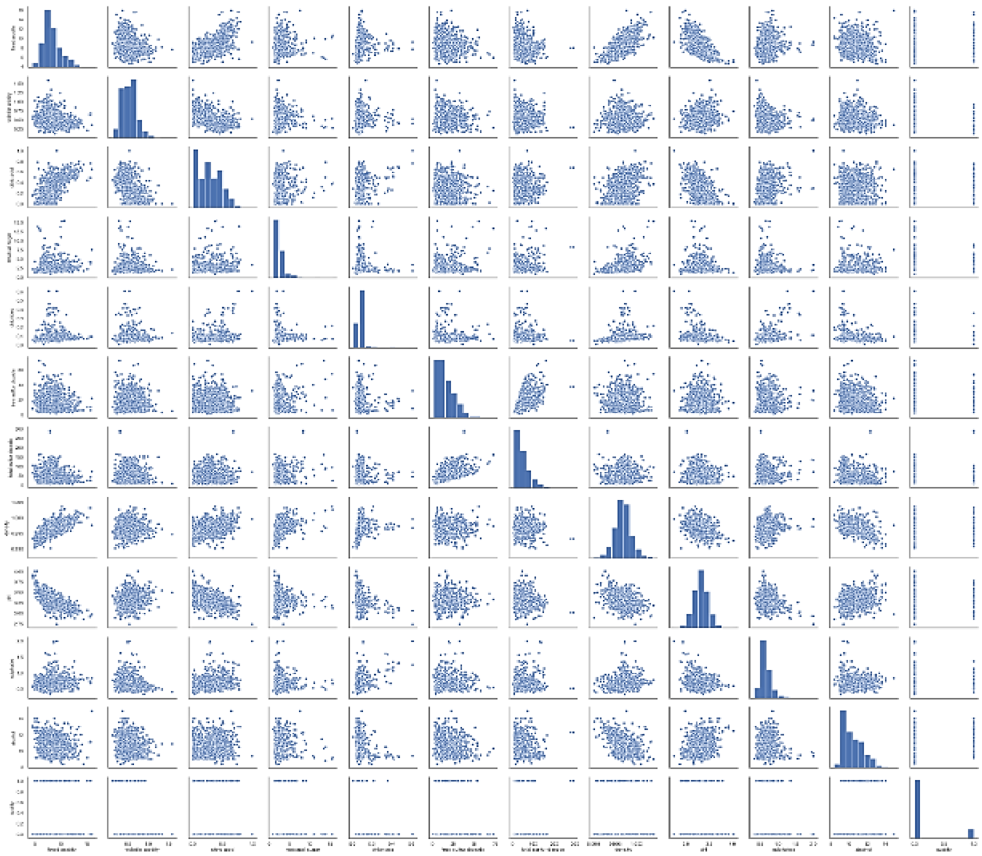
```
# Importing the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
%matplotlib inline
import time
import random

random.seed(100)

# Importing the dataset
wine = pd.read_csv('winequality-red.csv')

wine.head()

```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

3.Data preprocessing including visualization:

```
# #Making binary classificaion for the response variable.
from sklearn.preprocessing import LabelEncoder
bins = (2, 6.5, 8)
group_names = ['bad', 'good']
wine['quality'] = pd.cut(wine['quality'], bins = bins, labels = group_names)
label_quality = LabelEncoder()
wine['quality'] = label_quality.fit_transform(wine['quality'])
wine['quality'].value_counts()


#plotting the response variable
sns.countplot(wine['quality'])

```

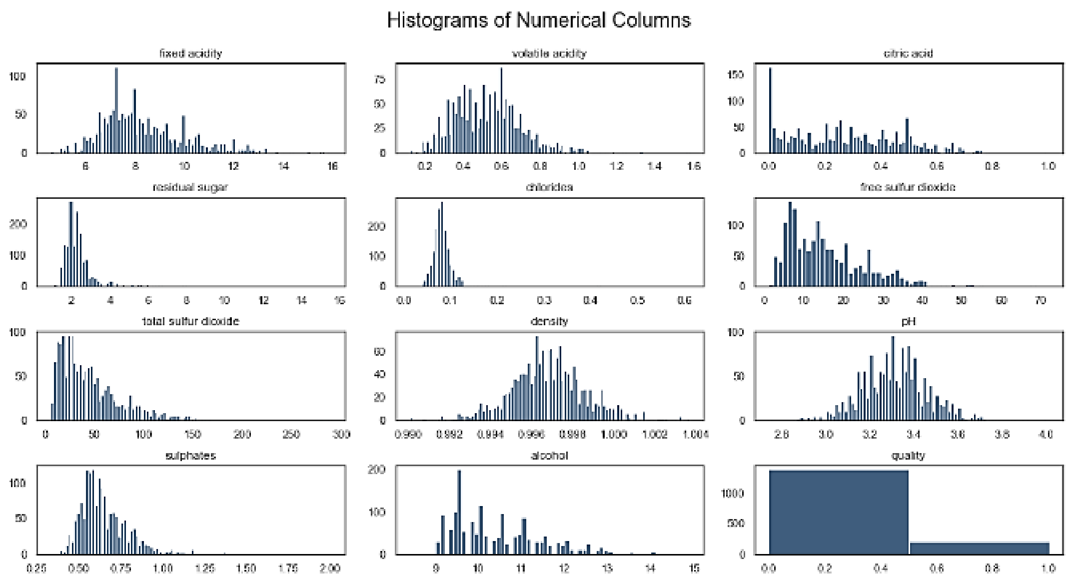




```python
wine[wine.columns[:11]].describe()
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000
mean	8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.467792	0.996747	3.311113	0.658149	10.422983
std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.895324	0.001887	0.154386	0.169507	1.065668
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000	0.990070	2.740000	0.330000	8.400000
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.000000	0.995600	3.210000	0.550000	9.500000
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.000000	0.996750	3.310000	0.620000	10.200000
75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.000000	0.997835	3.400000	0.730000	11.100000
max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.000000	1.003690	4.010000	2.000000	14.900000

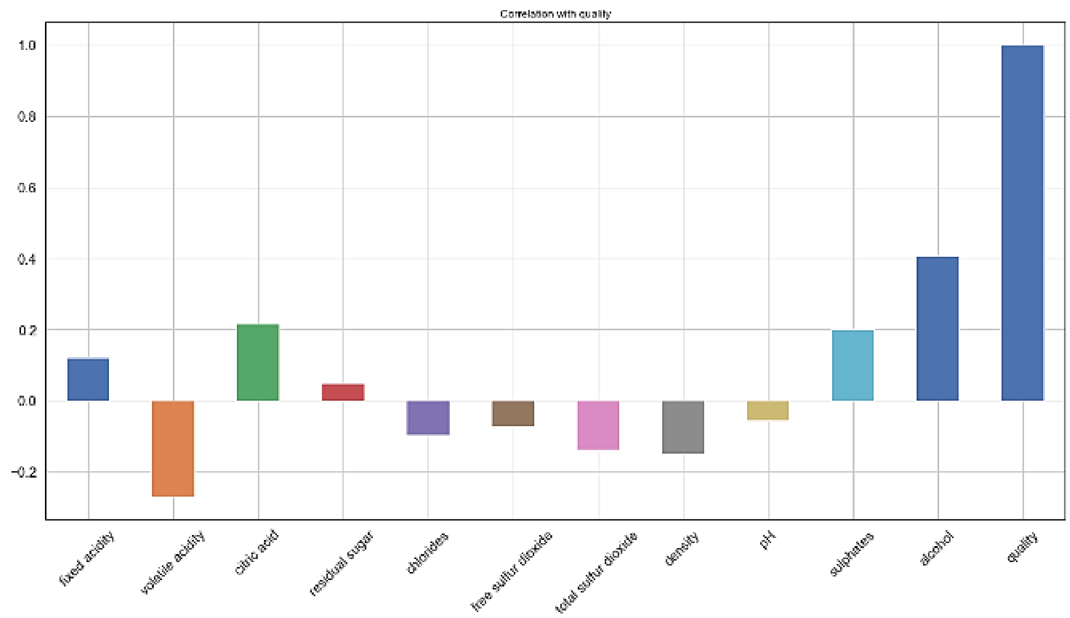
```python
## Histograms
fig = plt.figure(figsize=(15, 12))
plt.suptitle('Histograms of Numerical Columns', fontsize=20)
for i in range(wine.shape[1]):
    plt.subplot(6, 3, i + 1)
    f = plt.gca()
    f.set_title(wine.columns.values[i])

    vals = np.size(wine.iloc[:, i].unique())
    if vals >= 100:
        vals = 100

    plt.hist(wine.iloc[:, i], bins=vals, color='#3F5D7D')
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
```



```
wine.isna().any()
```

```
fixed acidity           False
volatile acidity        False
citric acid             False
residual sugar          False
chlorides               False
free sulfur dioxide     False
total sulfur dioxide    False
density                 False
pH                      False
sulphates               False
alcohol                 False
quality                 False
dtype: bool
```

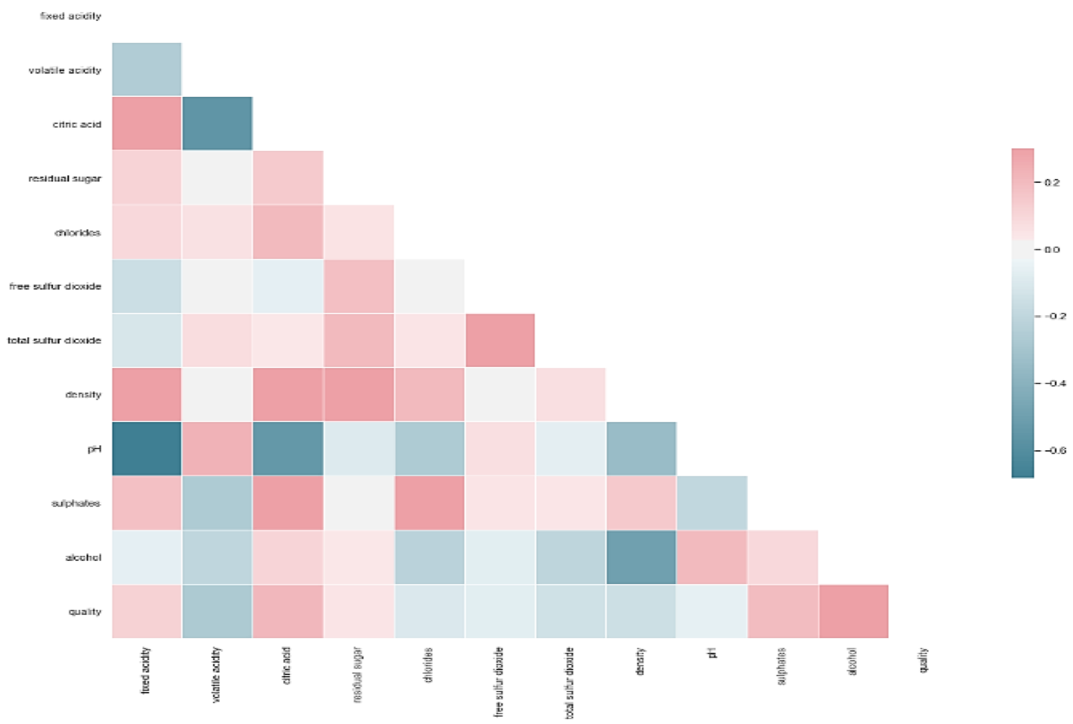
```
#Correlation with Quality with respect to attributes
wine.corrwith(wine.quality).plot.bar(
        figsize = (20, 10), title = "Correlation with quality", fontsize = 15,
        rot = 45, grid = True)
```



```
## Correlation Matrix

sns.set(style="white")

# Compute the correlation matrix
corr = wine.corr()

corr.head()
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
fixed acidity	1.000000	-0.256131	0.671703	0.114777	0.093705	-0.153794	-0.113181	0.668047	-0.682978	0.183006	-0.061668	0.120061
volatile acidity	-0.256131	1.000000	-0.552496	0.001918	0.061298	-0.010504	0.076470	0.022026	0.234937	-0.260987	-0.202288	-0.270712
citric acid	0.671703	-0.552496	1.000000	0.143577	0.203823	-0.060978	0.035533	0.364947	-0.541904	0.312770	0.109903	0.214716
residual sugar	0.114777	0.001918	0.143577	1.000000	0.055610	0.187049	0.203028	0.355283	-0.085652	0.005527	0.042075	0.047779
chlorides	0.093705	0.061298	0.203823	0.055610	1.000000	0.005562	0.047400	0.200632	-0.265026	0.371260	-0.221141	-0.097308

```

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(18, 15))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```



4.Machine Learning Model building:

```
#Assigning and dividing the dataset
X = wine.drop('quality',axis=1)
y=wine['quality']
X.head()

y.head()
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4

```
0    5
1    5
2    5
3    6
4    5
Name: quality, dtype: int64
```

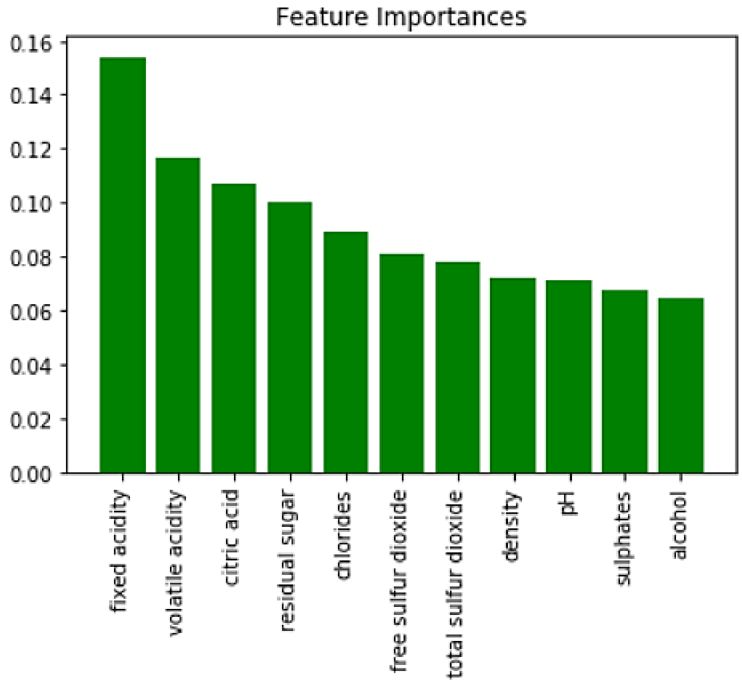
```

wine.columns[:11]

```

```
Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
       'pH', 'sulphates', 'alcohol'],
      dtype='object')
```

```
Fitting Random Forest Classification to the Training set
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(n_estimators = 200, criterion = 'entropy', random_state = 0)
classifier.fit(X, y)
importances = classifier.feature_importances_
indices = np. argsort(importances)[::-1]
for i in range(X.shape[1]):
    print ("%2d) %-*s %f" % (i + 1, 30, features_label[i],importances[indices[i]]))
```

```
 1) fixed acidity                  0.154052
 2) volatile acidity               0.116418
 3) citric acid                    0.107016
 4) residual sugar                 0.099913
 5) chlorides                      0.089030
 6) free sulfur dioxide            0.080517
 7) total sulfur dioxide           0.077752
 8) density                        0.072258
 9) pH                             0.071140
10) sulphates                      0.067320
11) alcohol                        0.064583
```

```python
title('Feature Importances')
plt.bar(range(X.shape[1]),importances[indices], color="green", align="center")
plt.xticks(range(X.shape[1]),features_label, rotation=90)
plt.xlim([-1, X.shape[1]])
plt.show()
```




```python
# Splitting the dataset into the Training set and Test set
from sklearn.model_selection  import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 5)

# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train2 = pd.DataFrame(sc.fit_transform(X_train))
X_test2 = pd.DataFrame(sc.transform(X_test))
X_train2.columns = X_train.columns.values
X_test2.columns = X_test.columns.values
X_train2.index = X_train.index.values
X_test2.index = X_test.index.values
X_train = X_train2
X_test = X_test2

#Using Principal Dimensional Reduction
from sklearn.decomposition import PCA
pca = PCA(n_components = 4)
X_train = pca.fit_transform(X_train)
X_test = pca.transform(X_test)
explained_variance = pca.explained_variance_ratio_
print(pd.DataFrame(explained_variance))
```

```
          0
0  0.281687
1  0.171462
2  0.143245
3  0.114765
```

```python
#### Model Building ####

### Comparing Models

## Logistic Regression
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0, penalty = 'l1')
classifier.fit(X_train, y_train)

# Predicting Test Set
y_pred = classifier.predict(X_test)
from sklearn.metrics import confusion_matrix, accuracy_score, f1_score, precision_score, recall_score
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

results = pd.DataFrame([['Logistic Regression', acc, prec, rec, f1]],
               columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Score'])
print(results)
```

	Model	Accuracy	Precision	Recall	F1 Score
0	Logistic Regression	0.86875	0.6	0.26087	0.363636

```python
## SVM (Linear)
from sklearn.svm import SVC
classifier = SVC(random_state = 0, kernel = 'linear')
classifier.fit(X_train, y_train)

# Predicting Test Set
y_pred = classifier.predict(X_test)
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

model_results = pd.DataFrame([['SVM (Linear)', acc, prec, rec, f1]],
               columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Score'])

results = results.append(model_results, ignore_index = True)
print(results)
```

	Model	Accuracy	Precision	Recall	F1 Score
0	Logistic Regression	0.86875	0.6	0.26087	0.363636
1	SVM (Linear)	0.85625	0.0	0.00000	0.000000

```python
## SVM (rbf)
from sklearn.svm import SVC
classifier = SVC(random_state = 0, kernel = 'rbf')
classifier.fit(X_train, y_train)

# Predicting Test Set
y_pred = classifier.predict(X_test)
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

model_results = pd.DataFrame([['SVM (RBF)', acc, prec, rec, f1]],
               columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Score'])

results = results.append(model_results, ignore_index = True)
print(results)
```

	Model	Accuracy	Precision	Recall	F1 Score
0	Logistic Regression	0.86875	0.600000	0.260870	0.363636
1	SVM (Linear)	0.85625	0.000000	0.000000	0.000000
2	SVM (RBF)	0.87500	0.714286	0.217391	0.333333

```python
## Randomforest
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(random_state = 0, n_estimators = 100,
                                    criterion = 'entropy')
classifier.fit(X_train, y_train)

# Predicting Test Set
y_pred = classifier.predict(X_test)
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

model_results = pd.DataFrame([['Random Forest (n=100)', acc, prec, rec, f1]],
               columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Score'])

results = results.append(model_results, ignore_index = True)
print(results)
```

	Model	Accuracy	Precision	Recall	F1 Score
0	Logistic Regression	0.868750	0.600000	0.260870	0.363636
1	SVM (Linear)	0.856250	0.000000	0.000000	0.000000
2	SVM (RBF)	0.875000	0.714286	0.217391	0.333333
3	Random Forest (n=100)	0.903125	0.741935	0.500000	0.597403

5.Evaluate the model:

```
## K-fold Cross Validation
from sklearn.model_selection import cross_val_score
accuracies = cross_val_score(estimator = classifier, X= X_train, y = y_train,
                             cv = 10)
print("Random Forest Classifier Accuracy: %0.2f (+/- %0.2f)"  % (accuracies.mean(), accuracies.std() * 2))
```

```
Random Forest Classifier Accuracy: 0.90 (+/- 0.05)
```

```
# Applying Grid Search

# Round 1: Entropy
parameters = {"max_depth": [3, None],

              'min_samples_split': [2, 5, 10],
              'min_samples_leaf': [1, 5, 10],
              "bootstrap": [True, False],
              "criterion": ["entropy"]}

from sklearn.model_selection import GridSearchCV
grid_search = GridSearchCV(estimator = classifier, # Make sure classifier points to the RF model
                           param_grid = parameters,
                           scoring = "accuracy",
                           cv = 10,
                           n_jobs = -1)

t0 = time.time()
grid_search = grid_search.fit(X_train, y_train)
t1 = time.time()
print("Took %0.2f seconds" % (t1 - t0))

rf_best_accuracy = grid_search.best_score_
rf_best_parameters = grid_search.best_params_
rf_best_accuracy, rf_best_parameters
```

```
Took 80.70 seconds

(0.8999218139171228,
 {'bootstrap': False,
  'criterion': 'entropy',
  'max_depth': None,
  'min_samples_leaf': 1,
  'min_samples_split': 2})
```

```
# Round 2: Entropy
parameters = {"max_depth": [None],

              'min_samples_split': [8, 10, 12],
              'min_samples_leaf': [1, 2, 3],
              "bootstrap": [True],
              "criterion": ["entropy"]}

from sklearn.model_selection import GridSearchCV
grid_search = GridSearchCV(estimator = classifier, # Make sure classifier points to the RF model
                           param_grid = parameters,
                           scoring = "accuracy",
                           cv = 10,
                           n_jobs = -1)

t0 = time.time()
grid_search = grid_search.fit(X_train, y_train)
t1 = time.time()
print("Took %0.2f seconds" % (t1 - t0))

rf_best_accuracy = grid_search.best_score_
rf_best_parameters = grid_search.best_params_
rf_best_accuracy, rf_best_parameters
```

```
Took 37.32 seconds

(0.8866301798279906,
 {'bootstrap': True,
  'criterion': 'entropy',
  'max_depth': None,
  'min_samples_leaf': 1,
  'min_samples_split': 8})
```

```python
# Round 1: Gini
parameters = {"max_depth": [3, None],

              'min_samples_split': [2, 5, 10],
              'min_samples_leaf': [1, 5, 10],
              "bootstrap": [True, False],
              "criterion": ["gini"]}
# Make sure classifier points to the RF model
from sklearn.model_selection import GridSearchCV
grid_search = GridSearchCV(estimator = classifier,
                           param_grid = parameters,
                           scoring = "accuracy",
                           cv = 10,
                           n_jobs = -1)

t0 = time.time()
grid_search = grid_search.fit(X_train, y_train)
t1 = time.time()
print("Took %0.2f seconds" % (t1 - t0))

rf_best_accuracy = grid_search.best_score_
rf_best_parameters = grid_search.best_params_
rf_best_accuracy, rf_best_parameters
```

```
Took 62.63 seconds

(0.9046129788897577,
 {'bootstrap': True,
  'criterion': 'gini',
  'max_depth': None,
  'min_samples_leaf': 1,
  'min_samples_split': 2})
```

```python
# Round 2: Gini
parameters = {"max_depth": [None],

              'min_samples_split': [2, 3, 4],
              'min_samples_leaf': [8, 10, 12],
              "bootstrap": [True],
              "criterion": ["gini"]}

from sklearn.model_selection import GridSearchCV
grid_search = GridSearchCV(estimator = classifier, # Make sure classifier points to the RF model
                           param_grid = parameters,
                           scoring = "accuracy",
                           cv = 10,
                           n_jobs = -1)

t0 = time.time()
grid_search = grid_search.fit(X_train, y_train)
t1 = time.time()
print("Took %0.2f seconds" % (t1 - t0))

rf_best_accuracy = grid_search.best_score_
rf_best_parameters = grid_search.best_params_
rf_best_accuracy, rf_best_parameters
```

```
Took 29.75 seconds

(0.8772478498827209,
 {'bootstrap': True,
  'criterion': 'gini',
  'max_depth': None,
  'min_samples_leaf': 8,
  'min_samples_split': 2})
```

```
rf_best_accuracy, rf_best_parameters
```

```
(0.9046129788897577,
 {'bootstrap': True,
  'criterion': 'gini',
  'max_depth': None,
  'min_samples_leaf': 1,
  'min_samples_split': 2})
```

6.Prediction results:

```
# Predicting Test Set
y_pred = grid_search.predict(X_test)
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

model_results = pd.DataFrame([['Random Forest (n=100, GSx2 + Gini)', acc, prec, rec, f1]],
               columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Score'])

results = results.append(model_results, ignore_index = True)
results
```

	Model	Accuracy	Precision	Recall	F1 Score
0	Logistic Regression	0.868750	0.600000	0.260870	0.363636
1	SVM (Linear)	0.856250	0.000000	0.000000	0.000000
2	SVM (RBF)	0.875000	0.714286	0.217391	0.333333
3	Random Forest (n=100)	0.903125	0.741935	0.500000	0.597403
4	Random Forest (n=100, GSx2 + Gini)	0.909375	0.757576	0.543478	0.632911
5	Random Forest (n=100, GSx2 + Gini)	0.909375	0.757576	0.543478	0.632911