Breast Cancer Classification Model

INTRODUCTION¶

Using the Breast Cancer Wisconsin Diagnostic Dataset, we assess the efficacy of several classification algorithms for breast cancer prediction in this article. The best model for classifying breast cancer will be determined by comparing the accuracy and other assessment criteria of several classifiers.

DATASET

Breast mass photos and the related diagnosis (Malignant or Benign) are used to construct features in the Breast Cancer Wisconsin Diagnostic Dataset. 80% of the data were utilised for training and 20% for testing after dividing the dataset into training and testing sets.

```
In [ ]:
```

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Loading the Dataset

| | Unnamed: 0 | x.radius_mean | x.texture_mean | x.perimeter_mean | x.area_mean | x.smoothness_mean | x.compactness_mean | x.concavity_mean | x.con |
|-----------------------|---------------|---------------|----------------|------------------|-------------|-------------------|--------------------|------------------|-------|
| 0 | 1 | 13.540 | 14.36 | 87.46 | 566.3 | 0.09779 | 0.08129 | 0.06664 | |
| 1 | 2 | 13.080 | 15.71 | 85.63 | 520.0 | 0.10750 | 0.12700 | 0.04568 | |
| 2 | 3 | 9.504 | 12.44 | 60.34 | 273.9 | 0.10240 | 0.06492 | 0.02956 | |
| 3 | 4 | 13.030 | 18.42 | 82.61 | 523.8 | 0.08983 | 0.03766 | 0.02562 | |
| 4 | 5 | 8.196 | 16.84 | 51.71 | 201.9 | 0.08600 | 0.05943 | 0.01588 | |
| | | | | | | | | | |
| 564 | 565 | 20.920 | 25.09 | 143.00 | 1347.0 | 0.10990 | 0.22360 | 0.31740 | |
| 565 | 566 | 21.560 | 22.39 | 142.00 | 1479.0 | 0.11100 | 0.11590 | 0.24390 | |
| 566 | 567 | 20.130 | 28.25 | 131.20 | 1261.0 | 0.09780 | 0.10340 | 0.14400 | |
| 567 | 568 | 16.600 | 28.08 | 108.30 | 858.1 | 0.08455 | 0.10230 | 0.09251 | |
| 568 | 569 | 20.600 | 29.33 | 140.10 | 1265.0 | 0.11780 | 0.27700 | 0.35140 | |
| 569 rows × 32 columns | | | | | | | | | |

Data Preprocessing

```
In [4]:
 1 # Check for missing values
 2 da.isnull().sum()
                       0
Unnamed: 0
                       0
x.radius_mean
x.texture_mean
{\tt x.perimeter\_mean}
x.area_mean
x.smoothness_mean
x.compactness mean
                       0
x.concavity mean
{\tt x.concave\_pts\_mean}
                       0
x.symmetry_mean
{\tt x.fractal\_dim\_mean}
                       0
x.radius_se
x.texture_se
x.perimeter_se
                       0
x.area se
x.smoothness se
x.compactness_se
x.concavity\_se
                       0
x.concave_pts_se
x.symmetry_se
x.fractal_dim_se
x.radius worst
x.texture worst
x.perimeter\_worst
x.area_worst
                       0
x.smoothness\_worst
x.compactness_worst
x.concavity_worst
                       0
x.concave\_pts\_worst
x.symmetry_worst
                       0
x.fractal_dim_worst
                       a
                       0
dtype: int64
In [6]:
 1 da = da.dropna()
 2
In [7]:
 1 X = da.drop('y', axis=1)
 2 y = da['y']
In [9]:
 1 from sklearn.preprocessing import LabelEncoder, StandardScaler
 2 label_encoder = LabelEncoder()
 3 y = label_encoder.fit_transform(y)
```

Splitting the Data

```
In [10]:

1    from sklearn.model_selection import train_test_split

In [12]:

1    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=50)
```

Feature Scaling

```
In [20]:

1  # Scale the features using StandardScaler
2  scaler = StandardScaler()
3  X_train_scaled = scaler.fit_transform(X_train)
4  X_test_scaled = scaler.transform(X_test)
```

Model Selection and Evaluation

```
In [ ]:

1
```

In [15]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, AdaBoostClassifier, ExtraTreesClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier

5
```

In [21]:

```
classifiers = [
    LogisticRegression(),
    RandomForestClassifier(),
    GradientBoostingClassifier(),
    SVC(),
    KNeighborsClassifier()]
```

In [23]:

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score
```

In [24]:

```
1
   # List to store model performance
   model_names = []
 2
   performance = []
4
   # Train and evaluate each classifier
5
   for classifier in classifiers:
 6
       # Train the model
8
       classifier.fit(X_train_scaled, y_train)
 9
       # Make predictions on the testing set
10
11
       predictions = classifier.predict(X_test_scaled)
12
       # Calculate evaluation metrics
13
14
       accuracy = accuracy_score(y_test, predictions)
15
       precision = precision_score(y_test, predictions)
16
       recall = recall_score(y_test, predictions)
       f1 = f1_score(y_test, predictions)
17
18
       roc_auc = roc_auc_score(y_test, predictions)
19
20
       # Store model performance
       model_names.append(classifier.__class__.__name_
21
22
       performance.append([accuracy, precision, recall, f1, roc_auc])
```

C:\Users\Harshith\anaconda03\lib\site-packages\sklearn\neighbors_classification.py:228: FutureWarning: Unlike other r eduction functions (e.g. `skew`, `kurtosis`), the default behavior of `mode` typically preserves the axis it acts alon g. In SciPy 1.11.0, this behavior will change: the default value of `keepdims` will become False, the `axis` over which the statistic is taken will be eliminated, and the value None will no longer be accepted. Set `keepdims` to True or False to avoid this warning.

mode, _ = stats.mode(_y[neigh_ind, k], axis=1)

Model Performance Comparison

```
In [27]:
```

```
performance_df = pd.DataFrame(performance, columns=['Accuracy', 'Precision', 'Recall', 'F1-Score', 'ROC AUC'], index=model_names
```

In [36]:

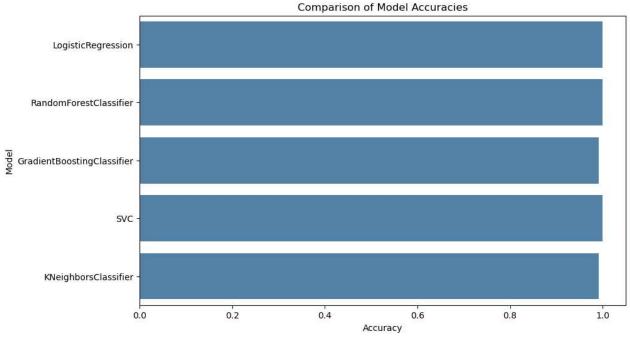
```
from tabulate import tabulate
print(f'\nResult\n')
print(tabulate(performance_df, headers='keys', tablefmt='psql'))
print()
```

Result

| | Accuracy | Precision | + Recall | F1-Score | ROC AUC |
|---|---|------------------------------|--|---|---|
| LogisticRegression RandomForestClassifier GradientBoostingClassifier SVC KNeighborsClassifier KNeighborsClassifier | 1 1 0.991228 1 0.991228 0.991228 | 1 1 0.979167 1 1 | 1 1 1 1 0.978723 0.978723 | 1 1 0.989474 1 0.989247 0.989247 | 1 1 0.992537 1 0.989362 0.989362 |

In [39]:

```
plt.figure(figsize=(10, 6))
sns.barplot(x=performance_df['Accuracy'], y=performance_df.index, color='steelblue')
plt.xlabel('Accuracy')
plt.ylabel('Model')
plt.title('Comparison of Model Accuracies')
plt.show()
```



| In []: | |
|---------|--|
| 1 | |
| In []: | |
| 1 | |