•[1]:
```
##1.Loading the dataset
## Import necessary libraries
import pandas as pd
from sklearn.datasets import load_breast_cancer

# Load the dataset
data = load_breast_cancer()

# Create a DataFrame
df = pd.DataFrame(data.data, columns=data.feature_names)
df['target'] = data.target

# Display basic info
print(df.info())
print(df.head())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   mean radius             569 non-null    float64
 1   mean texture            569 non-null    float64
 2   mean perimeter          569 non-null    float64
 3   mean area               569 non-null    float64
 4   mean smoothness         569 non-null    float64
 5   mean compactness        569 non-null    float64
 6   mean concavity          569 non-null    float64
 7   mean concave points     569 non-null    float64
 8   mean symmetry           569 non-null    float64
 9   mean fractal dimension  569 non-null    float64
 10  radius error            569 non-null    float64
```

```
 14  smoothness error         569 non-null    float64
 15  compactness error        569 non-null    float64
 16  concavity error          569 non-null    float64
 17  concave points error     569 non-null    float64
 18  symmetry error           569 non-null    float64
 19  fractal dimension error  569 non-null    float64
 20  worst radius             569 non-null    float64
 21  worst texture            569 non-null    float64
 22  worst perimeter          569 non-null    float64
 23  worst area               569 non-null    float64
 24  worst smoothness         569 non-null    float64
 25  worst compactness        569 non-null    float64
 26  worst concavity          569 non-null    float64
 27  worst concave points     569 non-null    float64
 28  worst symmetry           569 non-null    float64
 29  worst fractal dimension  569 non-null    float64
 30  target                   569 non-null    int32
dtypes: float64(30), int32(1)
memory usage: 135.7 KB
None
   mean radius  mean texture  mean perimeter  mean area  mean smoothness  \
0        17.99         10.38          122.80     1001.0          0.11840
1        20.57         17.77          132.90     1326.0          0.08474
2        19.69         21.25          130.00     1203.0          0.10960
3        11.42         20.38           77.58      386.1          0.14250
4        20.29         14.34          135.10     1297.0          0.10030

   mean compactness  mean concavity  mean concave points  mean symmetry  \
0           0.27760          0.3001              0.14710         0.2419
1           0.07864          0.0869              0.07017         0.1812
2           0.15990          0.1974              0.12790         0.2069
3           0.28390          0.2414              0.10520         0.2597
4           0.13280          0.1980              0.10430         0.1809
```

| | mean compactness | mean concavity | mean concave points | mean symmetry | \ |
|---|---|---|---|---|---|
| 0 | 0.27760 | 0.3001 | 0.14710 | 0.2419 | |
| 1 | 0.07864 | 0.0869 | 0.07017 | 0.1812 | |
| 2 | 0.15990 | 0.1974 | 0.12790 | 0.2069 | |
| 3 | 0.28390 | 0.2414 | 0.10520 | 0.2597 | |
| 4 | 0.13280 | 0.1980 | 0.10430 | 0.1809 | |

| | mean fractal dimension | ... | worst texture | worst perimeter | worst area | \ |
|---|---|---|---|---|---|---|
| 0 | 0.07871 | ... | 17.33 | 184.60 | 2019.0 | |
| 1 | 0.05667 | ... | 23.41 | 158.80 | 1956.0 | |
| 2 | 0.05999 | ... | 25.53 | 152.50 | 1709.0 | |
| 3 | 0.09744 | ... | 26.50 | 98.87 | 567.7 | |
| 4 | 0.05883 | ... | 16.67 | 152.20 | 1575.0 | |

| | worst smoothness | worst compactness | worst concavity | worst concave points | \ |
|---|---|---|---|---|---|
| 0 | 0.1622 | 0.6656 | 0.7119 | 0.2654 | |
| 1 | 0.1238 | 0.1866 | 0.2416 | 0.1860 | |
| 2 | 0.1444 | 0.4245 | 0.4504 | 0.2430 | |
| 3 | 0.2098 | 0.8663 | 0.6869 | 0.2575 | |
| 4 | 0.1374 | 0.2050 | 0.4000 | 0.1625 | |

| | worst symmetry | worst fractal dimension | target |
|---|---|---|---|
| 0 | 0.4601 | 0.11890 | 0 |
| 1 | 0.2750 | 0.08902 | 0 |
| 2 | 0.3613 | 0.08758 | 0 |
| 3 | 0.6638 | 0.17300 | 0 |
| 4 | 0.2364 | 0.07678 | 0 |

[5 rows x 31 columns]

[3]:
```
##2.Preprocessing the data
##1. Missing Values: Checked for missing values, although none were found.
##2. Scaling: Used StandardScaler to standardize the dataset, which is beneficial for models like k-NN and SVM.

# Check for missing values
print(df.isnull().sum())

# If there were missing values, you could handle them like this:
# df.fillna(df.mean(), inplace=True)  # Fill with mean values
```

```
mean radius              0
mean texture             0
mean perimeter           0
mean area                0
mean smoothness          0
mean compactness         0
mean concavity           0
mean concave points      0
mean symmetry            0
mean fractal dimension   0
radius error             0
texture error            0
perimeter error          0
area error               0
smoothness error         0
compactness error        0
concavity error          0
concave points error     0
symmetry error           0
fractal dimension error  0
worst radius             0
worst texture            0
worst perimeter          0
worst area               0
worst smoothness         0
```

```
worst smoothness           0
worst compactness          0
worst concavity            0
worst concave points       0
worst symmetry             0
worst fractal dimension    0
target                     0
dtype: int64
```

[5]:

```
from sklearn.preprocessing import StandardScaler

# Separate features and target
X = df.drop('target', axis=1)
y = df['target']

# Scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Convert back to DataFrame for readability
X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)
print(X_scaled_df.head())
```

```
   mean radius  mean texture  mean perimeter  mean area  mean smoothness  \
0     1.097064     -2.073335        1.269934   0.984375         1.568466
1     1.829821     -0.353632        1.685955   1.908708        -0.826962
2     1.579888      0.456187        1.566503   1.558884         0.942210
3    -0.768909      0.253732       -0.592687  -0.764464         3.283553
4     1.750297     -1.151816        1.776573   1.826229         0.280372

   mean compactness  mean concavity  mean concave points  mean symmetry  \
0          3.283515        2.652874             2.532475       2.217515
1         -0.487072       -0.023846             0.548144       0.001392
2          1.052926        1.363478             2.037231       0.939685
3          3.402909        1.915897             1.451707       2.867383
4          0.539340        1.371011             1.428493      -0.009560
```

| | mean fractal dimension | ... | worst radius | worst texture | worst perimeter | \ |
|---|---|---|---|---|---|---|
| 0 | 2.255747 | ... | 1.886690 | -1.359293 | 2.303601 | |
| 1 | -0.868652 | ... | 1.805927 | -0.369203 | 1.535126 | |
| 2 | -0.398008 | ... | 1.511870 | -0.023974 | 1.347475 | |
| 3 | 4.910919 | ... | -0.281464 | 0.133984 | -0.249939 | |
| 4 | -0.562450 | ... | 1.298575 | -1.466770 | 1.338539 | |

| | worst area | worst smoothness | worst compactness | worst concavity | \ |
|---|---|---|---|---|---|
| 0 | 2.001237 | 1.307686 | 2.616665 | 2.109526 | |
| 1 | 1.890489 | -0.375612 | -0.430444 | -0.146749 | |
| 2 | 1.456285 | 0.527407 | 1.082932 | 0.854974 | |
| 3 | -0.550021 | 3.394275 | 3.893397 | 1.989588 | |
| 4 | 1.220724 | 0.220556 | -0.313395 | 0.613179 | |

| | worst concave points | worst symmetry | worst fractal dimension |
|---|---|---|---|
| 0 | 2.296076 | 2.750622 | 1.937015 |
| 1 | 1.087084 | -0.243890 | 0.281190 |
| 2 | 1.955000 | 1.152255 | 0.201391 |
| 3 | 2.175786 | 6.046041 | 4.935010 |
| 4 | 0.729259 | -0.868353 | -0.397100 |

[5 rows x 30 columns]

[ ]:
```
##Classification of algorithms
1. Logistic Regression:
Used for binary classification problems.
Outputs probabilities of class membership.
Works well when classes are linearly separable.
2. Decision Tree:
A tree-like model that splits the data into branches.
Easy to interpret, but prone to overfitting.
3. Random Forest:
An ensemble of decision trees.
Reduces overfitting and improves accuracy.
4. Support Vector Machine (SVM):
```

4. Support Vector Machine (SVM):
Finds the optimal hyperplane to separate classes.
Effective for high-dimensional data.
5. k-Nearest Neighbors (k-NN):
Classifies samples based on the majority vote of k nearest neighbors.
Sensitive to feature scaling.

[6]:
```
# Import necessary libraries
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

# Initialize models
models = {
    "Logistic Regression": LogisticRegression(),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(),
    "SVM": SVC(),
    "k-NN": KNeighborsClassifier()
}

# Train and evaluate models
results = {}
```

```
# Train and evaluate models
results = {}

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    acc = accuracy_score(y_test, y_pred)
    report = classification_report(y_test, y_pred)

    results[name] = {
        "Accuracy": acc,
        "Report": report
    }
    print(f"\n{name} Accuracy: {acc:.4f}")
    print(report)
```

```
Logistic Regression Accuracy: 0.9737
              precision    recall  f1-score   support

           0       0.98      0.95      0.96        43
           1       0.97      0.99      0.98        71

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114


Decision Tree Accuracy: 0.9474
              precision    recall  f1-score   support

           0       0.93      0.93      0.93        43
           1       0.96      0.96      0.96        71
```

```
Decision Tree Accuracy: 0.9474
              precision    recall  f1-score   support

           0       0.93      0.93      0.93        43
           1       0.96      0.96      0.96        71

    accuracy                           0.95       114
   macro avg       0.94      0.94      0.94       114
weighted avg       0.95      0.95      0.95       114


Random Forest Accuracy: 0.9649
              precision    recall  f1-score   support

           0       0.98      0.93      0.95        43
           1       0.96      0.99      0.97        71

    accuracy                           0.96       114
   macro avg       0.97      0.96      0.96       114
weighted avg       0.97      0.96      0.96       114


SVM Accuracy: 0.9737
              precision    recall  f1-score   support

           0       0.98      0.95      0.96        43
           1       0.97      0.99      0.98        71

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114
```

```
k-NN Accuracy: 0.9474
              precision    recall  f1-score   support

           0       0.93      0.93      0.93        43
           1       0.96      0.96      0.96        71

    accuracy                           0.95       114
   macro avg       0.94      0.94      0.94       114
weighted avg       0.95      0.95      0.95       114
```

[7]:

```python
import matplotlib.pyplot as plt

# Extract accuracy scores
model_names = list(results.keys())
accuracy_scores = [results[name]["Accuracy"] for name in model_names]

# Plotting the accuracy comparison
plt.figure(figsize=(12, 6))
plt.bar(model_names, accuracy_scores, color='skyblue')
plt.title('Model Comparison - Accuracy Scores')
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.ylim(0, 1)
plt.show()

# Identify the best and worst performing models
best_model = max(results, key=lambda x: results[x]["Accuracy"])
worst_model = min(results, key=lambda x: results[x]["Accuracy"])

print(f"\nBest Performing Model: {best_model} - Accuracy: {results[best_model]['Accuracy']:.4f}")
print(f"Worst Performing Model: {worst_model} - Accuracy: {results[worst_model]['Accuracy']:.4f}")
```

```
k-NN Accuracy: 0.9474
              precision    recall  f1-score   support

           0       0.93      0.93      0.93        43
           1       0.96      0.96      0.96        71

    accuracy                           0.95       114
   macro avg       0.94      0.94      0.94       114
weighted avg       0.95      0.95      0.95       114
```

[7]:

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plt.ylim(0, 1)
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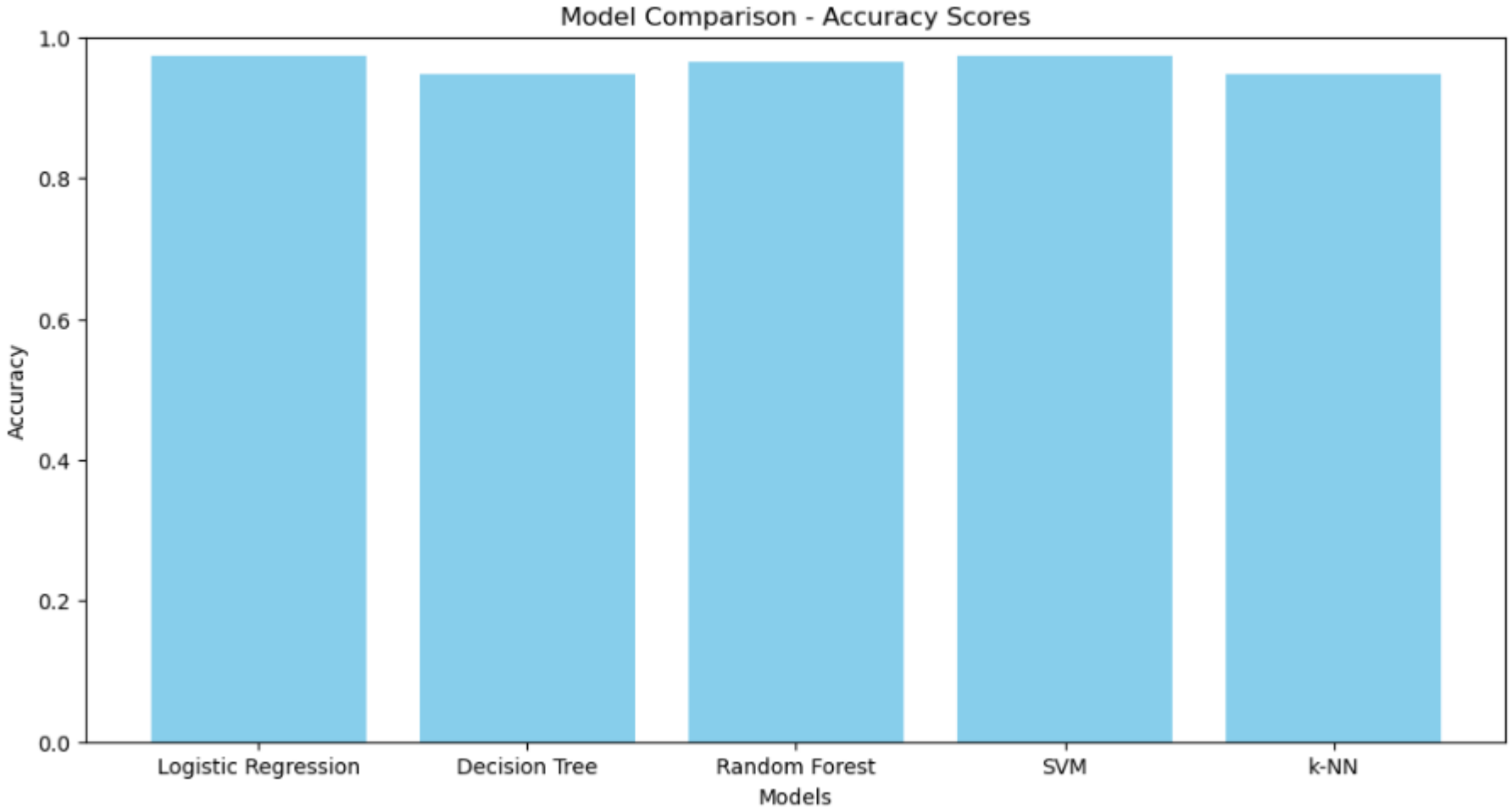
print(f"\nBest Performing Model: {best_model} - Accuracy: {results[best_model]['Accuracy']:.4f}")
print(f"Worst Performing Model: {worst_model} - Accuracy: {results[worst_model]['Accuracy']:.4f}")
```




```
Best Performing Model: Logistic Regression - Accuracy: 0.9737
Worst Performing Model: Decision Tree - Accuracy: 0.9474
```