```
In [2]: import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
         from sklearn.datasets import load breast cancer
In [4]: # Step 1: Load and Preprocess Data
         data = load breast cancer()
         df = pd.DataFrame(data.data, columns=data.feature_names)
         df['target'] = data.target
In [8]: df
Out[8]:
                                                                                         mean
               mean
                        mean
                                  mean
                                          mean
                                                       mean
                                                                     mean
                                                                               mean
                                                                                       concave
              radius texture perimeter
                                           area smoothness compactness concavity
                                                                                        points
               17.99
           0
                        10.38
                                  122.80 1001.0
                                                     0.11840
                                                                   0.27760
                                                                              0.30010
                                                                                       0.14710
               20.57
                        17.77
                                  132.90 1326.0
                                                     0.08474
                                                                   0.07864
                                                                              0.08690
                                                                                       0.07017
           2
               19.69
                        21.25
                                  130.00 1203.0
                                                     0.10960
                                                                   0.15990
                                                                              0.19740
                                                                                       0.12790
               11.42
                        20.38
                                   77.58
                                          386.1
                                                     0.14250
                                                                   0.28390
                                                                              0.24140
                                                                                       0.10520
           4
               20.29
                        14.34
                                  135.10 1297.0
                                                     0.10030
                                                                   0.13280
                                                                              0.19800
                                                                                       0.10430
         564
               21.56
                        22.39
                                                                              0.24390
                                                                                       0.13890
                                  142.00 1479.0
                                                     0.11100
                                                                   0.11590
         565
               20.13
                        28.25
                                  131.20 1261.0
                                                     0.09780
                                                                   0.10340
                                                                              0.14400
                                                                                       0.09791
         566
               16.60
                        28.08
                                  108.30
                                          858.1
                                                     0.08455
                                                                   0.10230
                                                                              0.09251
                                                                                       0.05302
         567
               20.60
                        29.33
                                  140.10 1265.0
                                                     0.11780
                                                                   0.27700
                                                                              0.35140
                                                                                       0.15200
         568
                                   47.92
                7.76
                        24.54
                                         181.0
                                                     0.05263
                                                                   0.04362
                                                                              0.00000
                                                                                       0.00000
        569 rows × 31 columns
In [6]: # Checking for missing values
         print("Missing values:")
         print(df.isnull().sum()) # No missing values
```

```
Missing values:
        mean radius
        mean texture
                                   0
                                   0
        mean perimeter
                                   0
        mean area
        mean smoothness
                                   0
        mean compactness
                                   0
        mean concavity
                                   0
        mean concave points
        mean symmetry
                                   0
        mean fractal dimension
                                   0
        radius error
                                   0
        texture error
                                   0
        perimeter error
                                   0
        area error
                                   0
                                   0
        smoothness error
        compactness error
                                   0
                                   0
        concavity error
        concave points error
                                   0
        symmetry error
        fractal dimension error
        worst radius
                                   0
                                   0
        worst texture
                                   0
        worst perimeter
        worst area
                                   0
        worst smoothness
        worst compactness
                                   0
        worst concavity
        worst concave points
                                   0
                                   0
        worst symmetry
        worst fractal dimension
                                   0
        target
        dtype: int64
In [10]: from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import StandardScaler
         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, confusion_matrix
In [12]: # Splitting the dataset into train and test
         X = df.drop(columns=['target'])
         y = df['target']
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
In [14]: # Feature scaling
         scaler = StandardScaler()
         X_train = scaler.fit_transform(X_train)
         X test = scaler.transform(X test)
In [16]: # Step 2: Classification Algorithm Implementation
         models = {
```

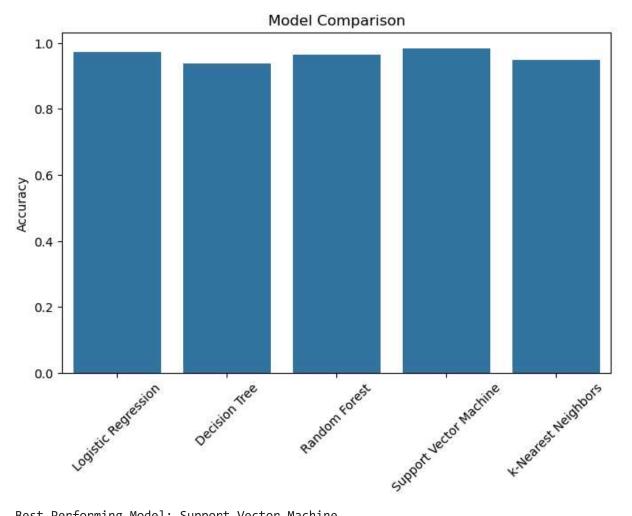
```
"Logistic Regression": LogisticRegression(),
             "Decision Tree": DecisionTreeClassifier(),
             "Random Forest": RandomForestClassifier(),
             "Support Vector Machine": SVC(),
             "k-Nearest Neighbors": KNeighborsClassifier()
         results = {}
In [18]: for name, model in models.items():
             model.fit(X_train, y_train)
             y_pred = model.predict(X_test)
             acc = accuracy_score(y_test, y_pred)
             results[name] = acc
             print(f"{name} Accuracy: {acc:.4f}")
             print(classification_report(y_test, y_pred))
             print("Confusion Matrix:")
             print(confusion_matrix(y_test, y_pred))
             print("-" * 50)
```

	uracy: 0.97		
precision	recall	f1-score	support
0.98	0.95	0.96	43
0.97	0.99	0.98	71
		0.97	114
0.97	0.97	0.97	114
0.97	0.97	0.97	114
rix:			
Accuracy:	0.9386		
		f1-score	support
0.91	0.93	0.92	43
0.96	0.94	0.95	71
		0.94	114
0.93	0.94	0.93	114
0.94	0.94	0.94	114
rix:			
Accuracy:	0.9649		
precision	recall	f1-score	support
0.98	0.93	0.95	43
0.96	0.99	0.97	71
		0.96	114
0.97	0.96	0.96	114
0.97	0.96	0.96	114
rix:			
r Machine A	Accuracy: 0	. 9825	
	-		support
1.00	0.95	0.98	43
			71
		0.98	114
0.99	0.98	0.98	114
0.98	0.98	0.98	114
rix:			
	precision 0.98 0.97 0.97 0.97 rix: Accuracy: precision 0.94 rix: Accuracy: precision 0.97 0.97 7.97 0.97 0.97 0.97 0.97	precision recall 0.98 0.95 0.97 0.99 0.97 0.97 0.97 0.97 rix: Accuracy: 0.9386 precision recall 0.91 0.93 0.96 0.94 0.93 0.94 0.94 0.94 rix: Accuracy: 0.9649 precision recall 0.98 0.99 0.97 0.96 0.97 0.96 rix: r Machine Accuracy: 0.969 rix: r Machine Accuracy: 0.969 0.97 0.96 rix: r Machine Accuracy: 0.969 0.97 0.96 0.97 0.96 0.97 0.96 0.97 0.96 0.98 0.98	### Precision recall f1-score 0.98

```
k-Nearest Neighbors 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
                           0.94
  macro avg
                0.94
                                    0.94
                                               114
weighted avg
                 0.95
                           0.95
                                    0.95
                                               114
Confusion Matrix:
[[40 3]
[ 3 68]]
```

```
In [20]: # Step 3: Model Comparison
    plt.figure(figsize=(8, 5))
    sns.barplot(x=list(results.keys()), y=list(results.values()))
    plt.xticks(rotation=45)
    plt.ylabel("Accuracy")
    plt.title("Model Comparison")
    plt.show()

    best_model = max(results, key=results.get)
    worst_model = min(results, key=results.get)
    print(f"Best Performing Model: {best_model}")
    print(f"Worst Performing Model: {worst_model}")
```



Best Performing Model: Support Vector Machine

Worst Performing Model: Decision Tree