Simple Classification of Wisconsin Breast Cancer Diagnostic Using Random Forest Algorithm

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DSF 35.0 - Data Science

ABOUT ME

Fresh graduate majoring in Agro-Industrial Technology from University of Darussalam Gontor, who have a strong interest in data analysis. Have a good understanding of basic concepts of statistics and machine learning.
Skilled in using MySQL, Python, Google Looker Studio, Google Colab, and Microsoft Power BI. Ready to learn and grow in the role of Data Analyst.

INTRODUCTION & OBJECTIVE

Wisconsin Breast Cancer Diagnostic is one of the toy datasets from scikit-learn. It’s a classic and very easy binary classification dataset. It has 569 instances, and attributes; including: 30 numeric, predictive attributes and the class.
The objective is to build a machine learning model for predicting whether a breast tumor is benign (0) or malignant (1) using Random Forest Algorithm.

TOOLS USED

pandas

seaborn

scikit learn

matplotlib

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INPUT DATA

```
[1] import pandas as pd
    from sklearn import datasets

    # Load the Wine dataset from scikit-learn and convert it to a DataFrame
    breast_cancer = datasets.load_breast_cancer()

    x = breast_cancer.data    # inputs for machine learning
    y = breast_cancer.target # desired output of machine learning

    # Convert feature and target data into a DataFrame
    df_x = pd.DataFrame(x, columns = breast_cancer.feature_names)
    df_y = pd.Series(y, name = 'target')

    # Combine features and targets in one DataFrames
    df = pd.concat([df_x, df_y], axis = 1)

    df.head(10)
```

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst texture	worst perimeter	worst area	worst smoothness	worst compactness	worst concavity	worst concave points	worst symmetry	worst fractal dimension	target
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.2419	0.07871	...	17.33	184.60	2019.0	0.1622	0.6656	0.7119	0.2654	0.4601	0.11890	0
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0.1812	0.05667	...	23.41	158.80	1956.0	0.1238	0.1866	0.2416	0.1860	0.2750	0.08902	0
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0.2069	0.05999	...	25.53	152.50	1709.0	0.1444	0.4245	0.4504	0.2430	0.3613	0.08758	0
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.2597	0.09744	...	26.50	98.87	567.7	0.2098	0.8663	0.6869	0.2575	0.6638	0.17300	0
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.1809	0.05883	...	16.67	152.20	1575.0	0.1374	0.2050	0.4000	0.1625	0.2364	0.07678	0
5	12.45	15.70	82.57	477.1	0.12780	0.17000	0.15780	0.08089	0.2087	0.07613	...	23.75	103.40	741.6	0.1791	0.5249	0.5355	0.1741	0.3985	0.12440	0
6	18.25	19.98	119.60	1040.0	0.09463	0.10900	0.11270	0.07400	0.1794	0.05742	...	27.66	153.20	1606.0	0.1442	0.2576	0.3784	0.1932	0.3063	0.08368	0
7	13.71	20.83	90.20	577.9	0.11890	0.16450	0.09366	0.05985	0.2196	0.07451	...	28.14	110.60	897.0	0.1654	0.3682	0.2678	0.1556	0.3196	0.11510	0
8	13.00	21.82	87.50	519.8	0.12730	0.19320	0.18590	0.09353	0.2350	0.07389	...	30.73	106.20	739.3	0.1703	0.5401	0.5390	0.2060	0.4378	0.10720	0
9	12.46	24.04	83.97	475.9	0.11860	0.23960	0.22730	0.08543	0.2030	0.08243	...	40.68	97.65	711.4	0.1853	1.0580	1.1050	0.2210	0.4366	0.20750	0

EXPLORATORY DATA ANALYSIS (EDA)

```
# View basic information about the data
df.info()
```

```
<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
 11  texture error            569 non-null    float64
 12  perimeter error          569 non-null    float64
 13  area 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    int64
dtypes: float64(30), int64(1)
memory usage: 137.9 KB
```

[3]
```
# Identify all the different numbers that appear in the 'target' column
df['target'].unique()
```

```
array([0, 1])
```

[4]
```
# View a statistical description of the data
df.describe()
```

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst texture	peri
count	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	...	569.000000	569.0
mean	14.127292	19.289649	91.969033	654.889104	0.096360	0.104341	0.088799	0.048919	0.181162	0.062798	...	25.677223	107.2
std	3.524049	4.301036	24.298981	351.914129	0.014064	0.052813	0.079720	0.038803	0.027414	0.007060	...	6.146258	33.6
min	6.981000	9.710000	43.790000	143.500000	0.052630	0.019380	0.000000	0.000000	0.106000	0.049960	...	12.020000	50.4
25%	11.700000	16.170000	75.170000	420.300000	0.086370	0.064920	0.029560	0.020310	0.161900	0.057700	...	21.080000	84.1
50%	13.370000	18.840000	86.240000	551.100000	0.095870	0.092630	0.061540	0.033500	0.179200	0.061540	...	25.410000	97.6
75%	15.780000	21.800000	104.100000	782.700000	0.105300	0.130400	0.130700	0.074000	0.195700	0.066120	...	29.720000	125.4
max	28.110000	39.280000	188.500000	2501.000000	0.163400	0.345400	0.426800	0.201200	0.304000	0.097440	...	49.540000	251.2

8 rows × 31 columns

DATA MODELLING

```
[5] from sklearn.model_selection import train_test_split

    # Split the data into train and test
    x_train, x_test, y_train, y_test = train_test_split(df_x, df_y, test_size = 0.2, random_state = 42)
```

```
[6] from sklearn.ensemble import RandomForestClassifier

    # Create and train a Random Forest model
    model = RandomForestClassifier(n_estimators=100, random_state=42)
    model.fit(x_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

```
[7] from sklearn.metrics import accuracy_score, classification_report

    # Predict and evaluate the model
    y_pred = model.predict(x_test)

    accuracy = accuracy_score(y_test, y_pred)

    print("Classification Report:")
    print(classification_report(y_test, y_pred))
    print(f"Accuracy: {accuracy * 100:.2f}%")
```

```
Classification Report:
              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

Accuracy: 96.49%
```

DATA VISUALIZATION
Distribution of Target Classes

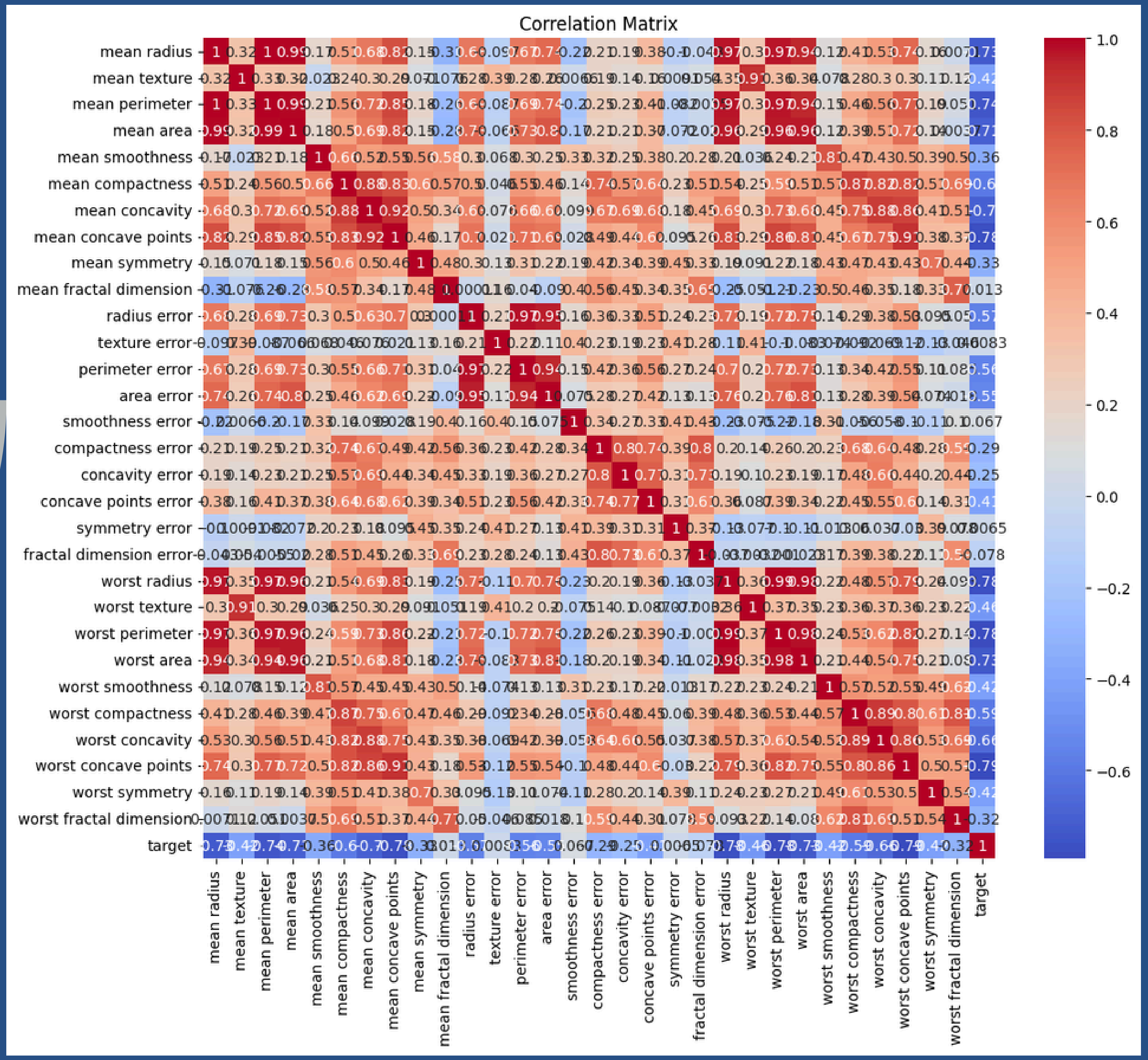
```
[8] import matplotlib.pyplot as plt
    import seaborn as sns

    # Visualize the distribution of target classes
    sns.countplot(x='target', data=df)
    plt.title('Distribution of Target Classes')
    plt.xlabel('Class (0: Benign, 1: Malignant)')
    plt.ylabel('Count')
    plt.show()
```

DATA VISUALIZATION

Correlation Matrix

```
[9]  # Visualize the correlation matrix
     plt.figure(figsize=(12, 10))
     sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
     plt.title('Correlation Matrix')
     plt.show()
```



DATA VISUALIZATION

Feature Importance

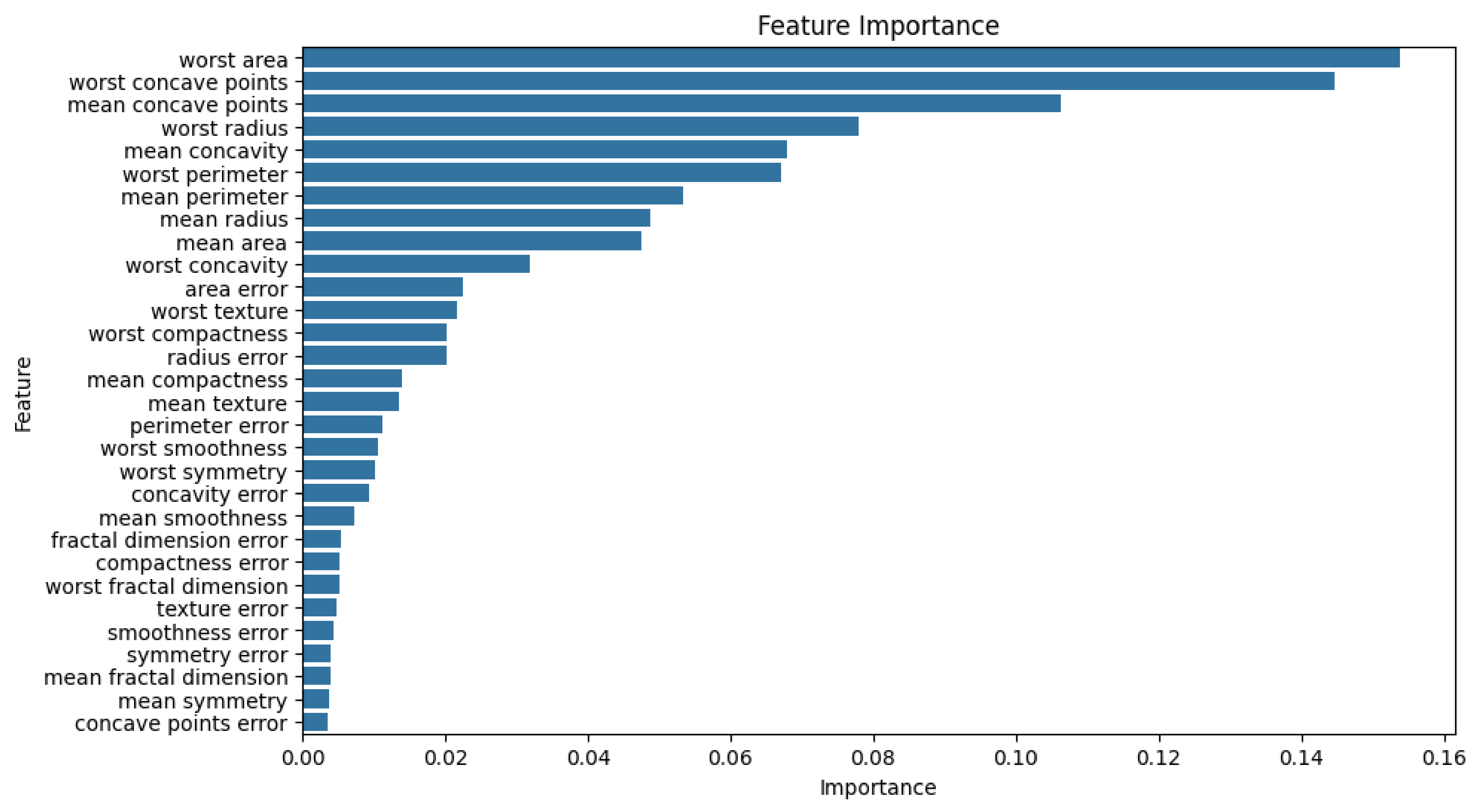
```
[10] # Visualize feature importance from the Random Forest model
     importances = model.feature_importances_

     # Access feature names from the breast_cancer dataset's feature_names attribute
     feature_names = breast_cancer.feature_names

     feature_importance_df = pd.DataFrame({'Feature': feature_names, 'Importance': importances})
     feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)

     plt.figure(figsize=(10, 6))
     sns.barplot(x='Importance', y='Feature', data=feature_importance_df)
     plt.title('Feature Importance')
     plt.xlabel('Importance')
     plt.ylabel('Feature')
     plt.show()
```

DATA VISUALIZATION
Feature Importance



THANK YOU

If you have any questions, suggestions or feedbacks, please do not hesitate to reach me through the contacts below:

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