In [156…

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import warnings
warnings.filterwarnings('ignore')
```

In [157…

```python
# Load the data
df = pd.read_csv('data.csv')
df
```

Out[157]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800
...	...	...	...	...	...	...	...	...	...
564	926424	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390
565	926682	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400
566	926954	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251
567	927241	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140
568	92751	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000

569 rows × 33 columns

In [158…

```python
df.head()
```

Out[158]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980

5 rows × 33 columns

In [159…

```python
df.tail()
```

Out[159]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean
564	926424	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390
565	926682	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400
566	926954	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251
567	927241	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140
568	92751	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000

5 rows × 33 columns

In [160…

```
df.isnull().sum()
```

Out[160]:

```
id                           0
diagnosis                    0
radius_mean                  0
texture_mean                 0
perimeter_mean               0
area_mean                    0
smoothness_mean              0
compactness_mean             0
concavity_mean               0
concave points_mean          0
symmetry_mean                0
fractal_dimension_mean       0
radius_se                    0
texture_se                   0
perimeter_se                 0
area_se                      0
smoothness_se                0
compactness_se               0
concavity_se                 0
concave points_se            0
symmetry_se                  0
fractal_dimension_se         0
radius_worst                 0
texture_worst                0
perimeter_worst              0
area_worst                   0
smoothness_worst             0
compactness_worst            0
concavity_worst              0
concave points_worst         0
symmetry_worst               0
fractal_dimension_worst      0
Unnamed: 32                569
dtype: int64
```

In [161…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 33 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   id                       569 non-null    int64  
 1   diagnosis                569 non-null    object 
 2   radius_mean              569 non-null    float64
 3   texture_mean             569 non-null    float64
 4   perimeter_mean           569 non-null    float64
 5   area_mean                569 non-null    float64
 6   smoothness_mean          569 non-null    float64
 7   compactness_mean         569 non-null    float64
 8   concavity_mean           569 non-null    float64
 9   concave points_mean      569 non-null    float64
 10  symmetry_mean            569 non-null    float64
 11  fractal_dimension_mean   569 non-null    float64
 12  radius_se                569 non-null    float64
 13  texture_se               569 non-null    float64
 14  perimeter_se             569 non-null    float64
 15  area_se                  569 non-null    float64
 16  smoothness_se            569 non-null    float64
 17  compactness_se           569 non-null    float64
 18  concavity_se             569 non-null    float64
 19  concave points_se        569 non-null    float64
 20  symmetry_se              569 non-null    float64
 21  fractal_dimension_se     569 non-null    float64
 22  radius_worst             569 non-null    float64
 23  texture_worst            569 non-null    float64
 24  perimeter_worst          569 non-null    float64
 25  area_worst               569 non-null    float64
 26  smoothness_worst         569 non-null    float64
 27  compactness_worst        569 non-null    float64
 28  concavity_worst          569 non-null    float64
 29  concave points_worst     569 non-null    float64
 30  symmetry_worst           569 non-null    float64
 31  fractal_dimension_worst  569 non-null    float64
 32  Unnamed: 32              0 non-null      float64
dtypes: float64(31), int64(1), object(1)
memory usage: 146.8+ KB
```

In [162…

```python
df.describe()
```

Out[162]:

	id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	po
count	5.690000e+02	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	5
mean	3.037183e+07	14.127292	19.289649	91.969033	654.889104	0.096360	0.104341	0.088799	
std	1.250206e+08	3.524049	4.301036	24.298981	351.914129	0.014064	0.052813	0.079720	
min	8.670000e+03	6.981000	9.710000	43.790000	143.500000	0.052630	0.019380	0.000000	
25%	8.692180e+05	11.700000	16.170000	75.170000	420.300000	0.086370	0.064920	0.029560	
50%	9.060240e+05	13.370000	18.840000	86.240000	551.100000	0.095870	0.092630	0.061540	
75%	8.813129e+06	15.780000	21.800000	104.100000	782.700000	0.105300	0.130400	0.130700	
max	9.113205e+08	28.110000	39.280000	188.500000	2501.000000	0.163400	0.345400	0.426800	

8 rows × 32 columns

In [163…

```python
print("Number of rows",df.shape[0])
print("Number of columns",df.shape[1])
```

```
Number of rows 569
Number of columns 33
```

In [164…

```python
print(df.duplicated().sum())
```

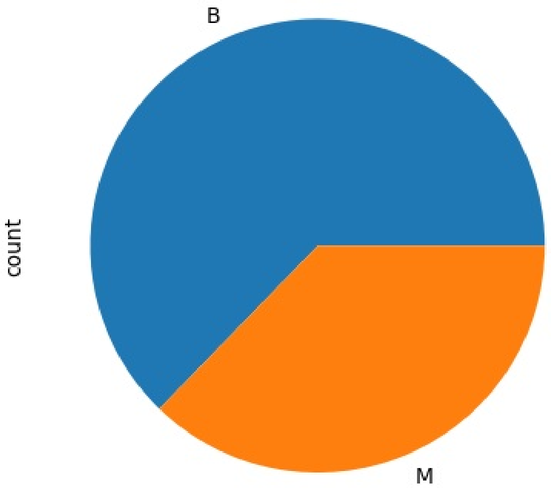
```
0
```

In [165…

```python
#visualization
df['diagnosis'].value_counts().plot(kind='pie')
```

Out[165]:

```
<Axes: ylabel='count'>
```



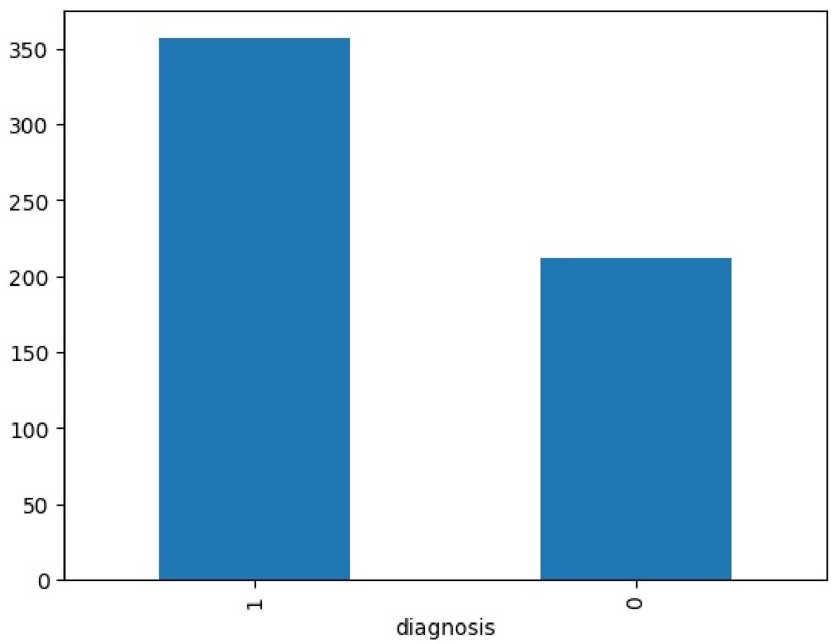

```
In [166…: # Data Preprocessing
df['diagnosis'] = df['diagnosis'].map({"B": 1, "M": 0})
```

```
In [167…: df['diagnosis'].value_counts()
```

```
Out[167]: diagnosis
1    357
0    212
Name: count, dtype: int64
```

```
In [168…: #visualization using barplot
df['diagnosis'].value_counts().plot(kind='bar')
```

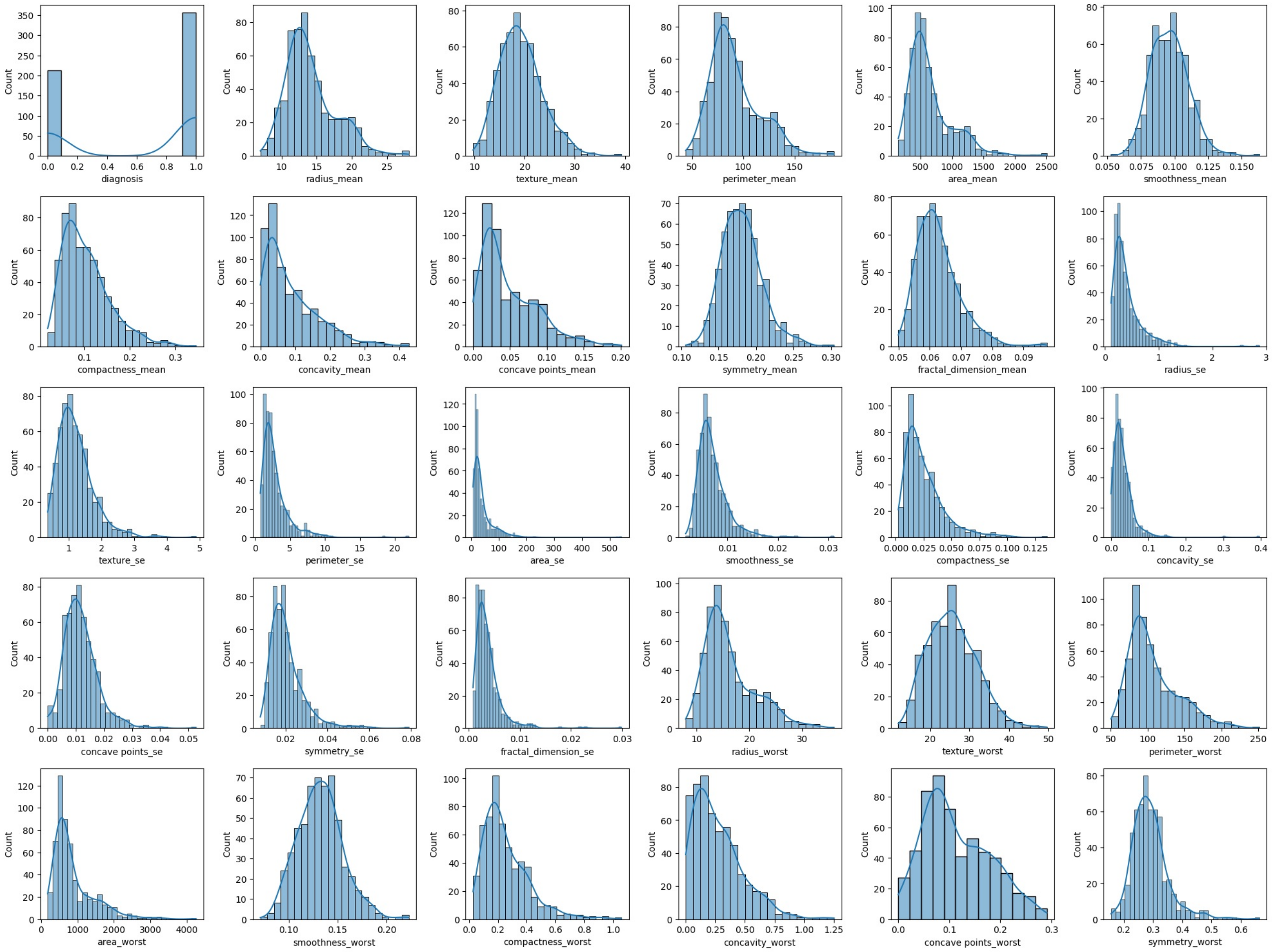
```
Out[168]: <Axes: xlabel='diagnosis'>
```




```
In [169…: #drop unnecessary feature
df.drop(['id', 'Unnamed: 32'], axis=1, inplace=True)
```

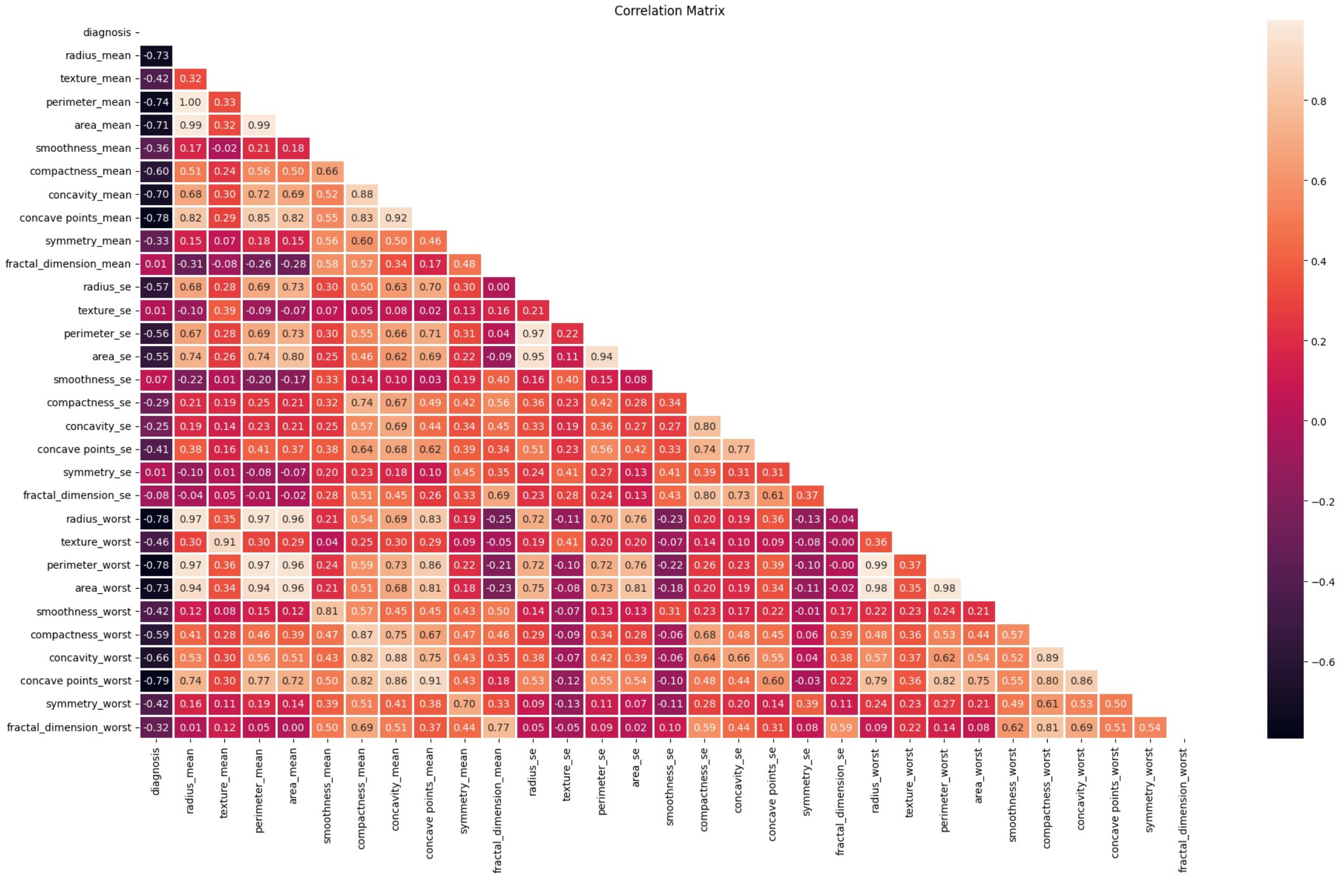
```
In [170…: # Visualize the distribution of features
plt.figure(figsize=(20, 15))
plotnumber = 1
for column in df.columns:
    if plotnumber <= 30:
```

```
        ax = plt.subplot(5, 6, plotnumber)
        sns.histplot(df[column], kde=True)
        plt.xlabel(column)
    plotnumber += 1
plt.tight_layout()
plt.show()
```



In [171…

```
# Heatmap of correlations
plt.figure(figsize=(20, 12))
corr = df.corr()
mask = np.triu(np.ones_like(corr, dtype=bool))
sns.heatmap(corr, mask=mask, linewidths=1, annot=True, fmt=".2f")
plt.title("Correlation Matrix")
plt.tight_layout()
plt.show()
```



In [172…

```
# Drop highly correlated features
corr_matrix = df.corr().abs()
mask = np.triu(np.ones_like(corr_matrix, dtype=bool))
tri_df = corr_matrix.mask(mask)
to_drop = [x for x in tri_df.columns if any(tri_df[x] > 0.92)]
df.drop(to_drop, axis=1, inplace=True)
print(f"Number of features after dropping correlated ones: {df.shape[1]}")
```

```
Number of features after dropping correlated ones: 23
```

In [173…

```
# Prepare data for training
X = df.drop('diagnosis', axis=1)
y = df['diagnosis']
```

In [174…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [175…

```
# Define models
models = [
    ("Logistic Regression", LogisticRegression(max_iter=200)),
    ("Random Forest", RandomForestClassifier(random_state=42)),
    ("K-Nearest Neighbors", KNeighborsClassifier()),
    ("Decision Tree", DecisionTreeClassifier(random_state=42)),
]
```

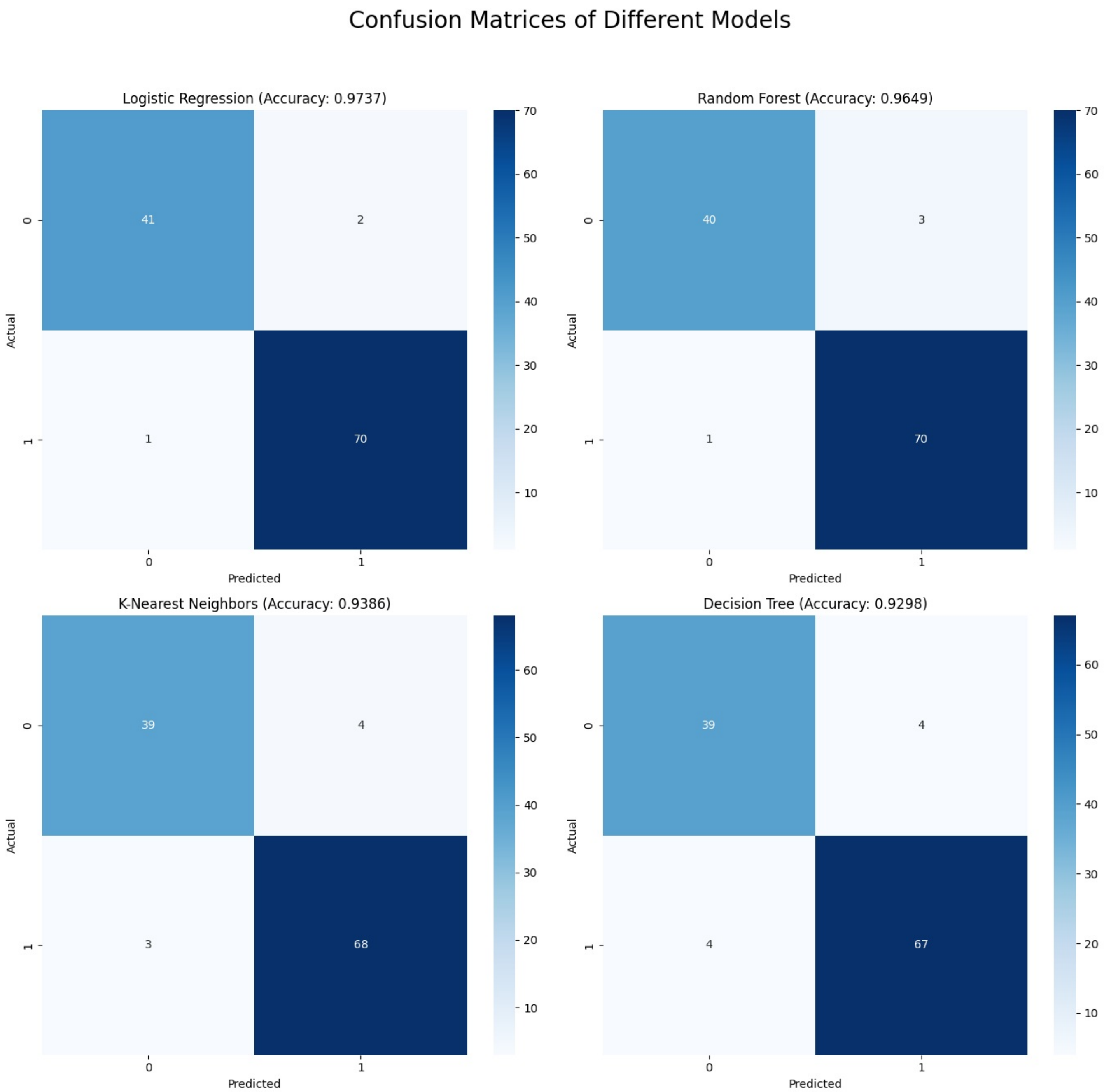
In [176…

```
# Train and evaluate models, storing results
results = {}
for name, model in models:
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    accuracy = accuracy_score(y_test, predictions)
    conf_matrix = confusion_matrix(y_test, predictions)

    results[name] = {
        "Accuracy": accuracy,
        "Confusion Matrix": conf_matrix
    }

    # Print results for each model
    print(f"{name} Accuracy: {accuracy:.4f}")
    print(classification_report(y_test, predictions, target_names=["Malignant", "Benign"]))
    print("-" * 50)
```

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

   Malignant       0.98      0.95      0.96        43
      Benign       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

--------------------------------------------------
Random Forest Accuracy: 0.9649
              precision    recall  f1-score   support

   Malignant       0.98      0.93      0.95        43
      Benign       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

--------------------------------------------------
K-Nearest Neighbors Accuracy: 0.9386
              precision    recall  f1-score   support

   Malignant       0.93      0.91      0.92        43
      Benign       0.94      0.96      0.95        71

    accuracy                           0.94       114
   macro avg       0.94      0.93      0.93       114
weighted avg       0.94      0.94      0.94       114

--------------------------------------------------
Decision Tree Accuracy: 0.9298
              precision    recall  f1-score   support

   Malignant       0.91      0.91      0.91        43
      Benign       0.94      0.94      0.94        71

    accuracy                           0.93       114
   macro avg       0.93      0.93      0.93       114
weighted avg       0.93      0.93      0.93       114

--------------------------------------------------
```

In [177…

```python
# Plot the confusion matrices
fig, axes = plt.subplots(2, 2, figsize=(14, 14))
fig.suptitle('Confusion Matrices of Different Models', fontsize=20)

for (name, result), ax in zip(results.items(), axes.flatten()):
    sns.heatmap(result['Confusion Matrix'], annot=True, fmt='d', cmap='Blues', ax=ax)
    ax.set_title(f'{name} (Accuracy: {result["Accuracy"]:.4f})')
    ax.set_xlabel('Predicted')
    ax.set_ylabel('Actual')

plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```



In [ ]:

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