AIM:- Implementation of Logistic and Multivariate Regression (A linear regression model that involves multiple independent variables (features) to predict a single dependent variable).

1. **Implement Logistic Regression on Cancer dataset and print the confusion matrix**.

In [1]:
```
import pandas as pd
```

In [2]:
```
# Data Collection
df = pd.read_csv("..//breast-cancer.csv")
# Display the first few rows of the dataset to inspect its structu
print("First 5 rows of the Breast_Cancer dataset:-\n", df.head())
```

```
First 5 rows of the Breast_Cancer dataset:-
          id diagnosis  radius_mean  texture_mean  perimeter_mean
area_mean \
0    842302         M        17.99         10.38          122.80
1001.0
1    842517         M        20.57         17.77          132.90
1326.0
2  84300903         M        19.69         21.25          130.00
1203.0
3  84348301         M        11.42         20.38           77.58
386.1
4  84358402         M        20.29         14.34          135.10
1297.0
```

```
   smoothness_mean  compactness_mean  concavity_mean  concave poin
ts_mean  \
0          0.11840           0.27760          0.3001
0.14710
1          0.08474           0.07864          0.0869
0.07017
2          0.10960           0.15990          0.1974
0.12790
3          0.14250           0.28390          0.2414
0.10520
4          0.10030           0.13280          0.1980
0.10430

   ...  radius_worst  texture_worst  perimeter_worst  area_worst
\
0  ...         25.38          17.33           184.60      2019.0
1  ...         24.99          23.41           158.80      1956.0
2  ...         23.57          25.53           152.50      1709.0
3  ...         14.91          26.50            98.87       567.7
4  ...         22.54          16.67           152.20      1575.0

   smoothness_worst  compactness_worst  concavity_worst  concave p
oints_worst  \
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

   symmetry_worst  fractal_dimension_worst
0          0.4601                  0.11890
1          0.2750                  0.08902
2          0.3613                  0.08758

3          0.6638                  0.17300
4          0.2364                  0.07678

[5 rows x 32 columns]
```

In [3]:
```
# Check the dimensions of the dataset (number of rows and columns)
row, col = df.shape
print("No. of rows in the dataset: ", row)
print("No. of column in the dataset: ", col)
```

```
No. of rows in the dataset: 569
No. of column in the dataset: 32
```

In [4]:
```
# Identify the data types of each column (numeric, categorical, te
print("Data types of each column:\n", df.dtypes)
```

```
Data types of each column:
 id                             int64
diagnosis                     object
radius_mean                  float64
texture_mean                 float64
perimeter_mean               float64
area_mean                    float64
smoothness_mean              float64
compactness_mean             float64
concavity_mean               float64
concave points_mean          float64
symmetry_mean                float64
fractal_dimension_mean       float64
radius_se                    float64
texture_se                   float64
perimeter_se                 float64
area_se                      float64
smoothness_se                float64
compactness_se               float64
concavity_se                 float64
concave points_se            float64
symmetry_se                  float64
fractal_dimension_se         float64
radius_worst                 float64
texture_worst                float64
perimeter_worst              float64
area_worst                   float64
smoothness_worst             float64
compactness_worst            float64
concavity_worst              float64
concave points_worst         float64
symmetry_worst               float64
fractal_dimension_worst      float64
dtype: object
```

In [5]:
```
# Data Preprocessing
# Display the number of missing values in each column
```

```
missingValues = df.isnull().sum()
print("Missing values per column:-")
print(missingValues)
```

```
Missing values per column:-
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
dtype: int64
```

In [6]:
```
# Finding Unique categories of diagnosis column
print("Types of Cancer: ", df['diagnosis'].unique())
```

```
Types of Cancer:  ['M' 'B']
```

In [7]:
```
# Mapping with integer values
df['diagnosis'] = df['diagnosis'].map({'M': 0, 'B': 1})
print("Checking Dataset after mapping:-\n", df.head())
```

```
Checking Dataset after mapping:-
         id diagnosis  radius_mean  texture_mean  perimeter_mean
area_mean \
0    842302         0        17.99         10.38          122.80
1001.0
1    842517         0        20.57         17.77          132.90
1326.0
2  84300903         0        19.69         21.25          130.00
1203.0
3  84348301         0        11.42         20.38           77.58
386.1
4  84358402         0        20.29         14.34          135.10
1297.0

   smoothness_mean  compactness_mean  concavity_mean  concave poin
ts_mean  \
0          0.11840           0.27760          0.3001
0.14710
1          0.08474           0.07864          0.0869
0.07017
2          0.10960           0.15990          0.1974
0.12790
3          0.14250           0.28390          0.2414
0.10520
4          0.10030           0.13280          0.1980
0.10430

   ...  radius_worst  texture_worst  perimeter_worst  area_worst
\
0  ...         25.38          17.33           184.60      2019.0
1  ...         24.99          23.41           158.80      1956.0
2  ...         23.57          25.53           152.50      1709.0
3  ...         14.91          26.50            98.87       567.7
4  ...         22.54          16.67           152.20      1575.0

   smoothness_worst  compactness_worst  concavity_worst  concave p
oints_worst  \
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

   symmetry_worst  fractal_dimension_worst
0          0.4601                  0.11890
1          0.2750                  0.08902
```

```
2          0.3613                     0.08758
3          0.6638                     0.17300
4          0.2364                     0.07678

[5 rows x 32 columns]
```

In [8]:
```
# Split the dataset into independent and dependent feature
X = df.iloc[:, 1:]  # features
y = df.iloc[:, 1]  # target variable    (diagnosis: 2nd column)
```

In [9]:
```
from sklearn.model_selection import train_test_split
# Split the dataset into training and testing sets(75% training, 2
X_train, X_test, y_train, y_test = train_test_split(X, y, test_siz
```

In [10]:
```
from sklearn.preprocessing import StandardScaler
# Scale the input features using StandardScaler
scaler = StandardScaler()
X_train_scaled  = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [11]:
```
from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression()
```

In [12]:
```
from sklearn.model_selection import GridSearchCV
# GridSearchCV is used to tune the hyperparameters
parameter = {'penalty': ['l2'], 'C': [1, 2, 3, 4, 5, 6, 10, 20, 30
# Scoring parameters for classification is 'accuracy'
classifier_regressor  = GridSearchCV(classifier, param_grid=paramet
```

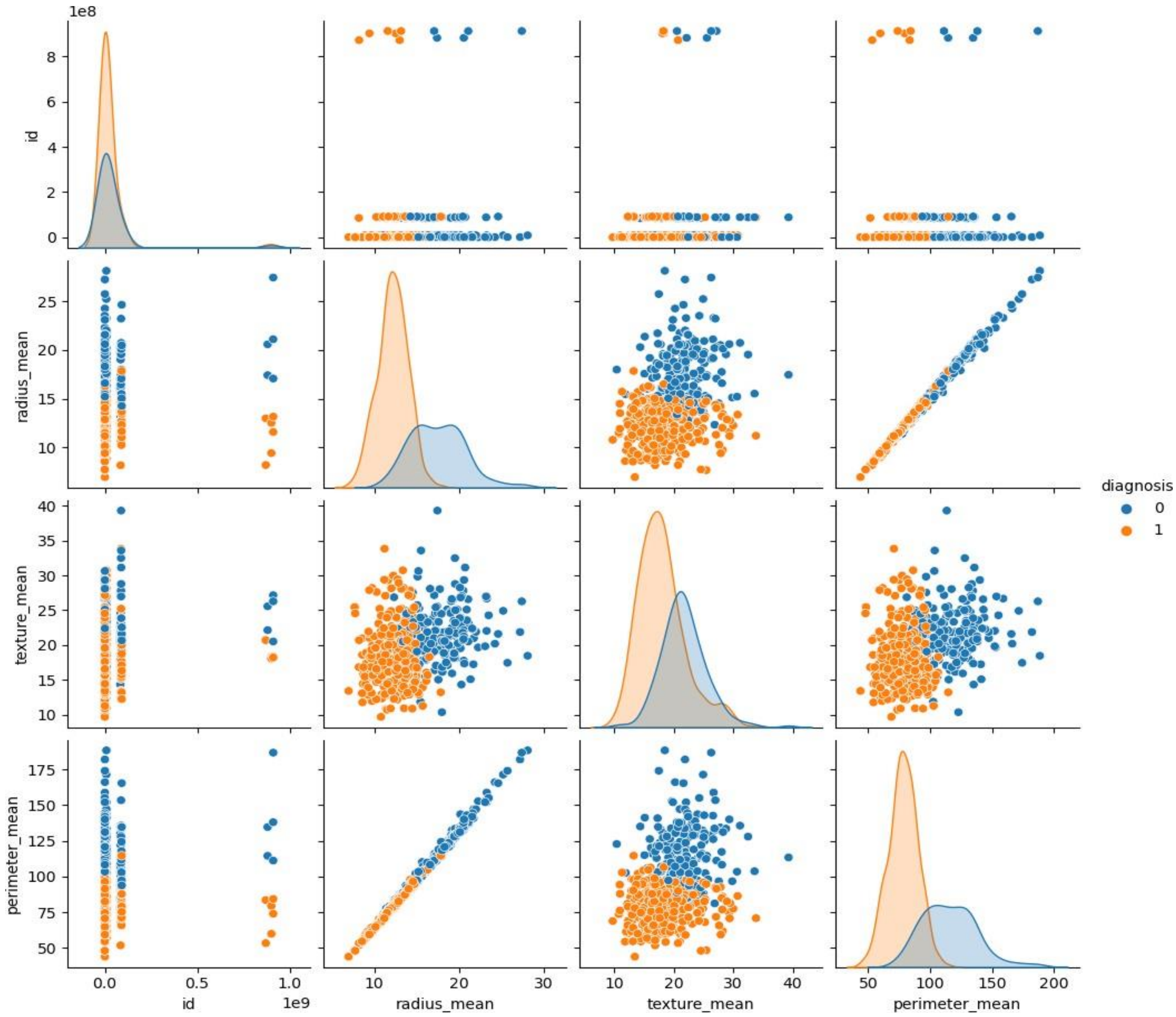
In [13]:
```
classifier_regressor.fit(X_train_scaled,  y_train)
print("Best parameters for classifier:\n", classifier_regressor.be
# Best Score
print("Best Score is: ", classifier_regressor.best_score_)
```

```
Best parameters for classifier:
 {'C': 20, 'max_iter': 100, 'penalty': 'l2'}
Best Score is: 1.0
```

In [14]:
```
# Make predictions on the scaled test data
y_predict  = classifier_regressor.predict(X_test_scaled)
```

In [15]:
```
import seaborn as sns
# Create a pair plot to visualize the data
# Taking sample subset of the dataset to avoid intensive computati
df_sample = df.iloc[:, :5]       # (first 5 columns)
sns.pairplot(df_sample,  hue='diagnosis')
```

Out[15]:
```
<seaborn.axisgrid.PairGrid at 0x1dd488a0d90>
```



In [16]:
```python
from sklearn.metrics import confusion_matrix
# Calculate the confusion matrix
conf_matrix = confusion_matrix(y_test, y_predict)
print("Confusion Matrix is:\n", conf_matrix)
```

```
Confusion Matrix is:
 [[54  0]
 [ 0 89]]
```

In [17]:
```python
from sklearn.metrics import classification_report
print(classification_report(y_predict, y_test))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        54
           1       1.00      1.00      1.00        89

    accuracy                           1.00       143
   macro avg       1.00      1.00      1.00       143
weighted avg       1.00      1.00      1.00       143
```

2. Apply Multivariate regression on Boston Housing Rate Dataset to predict house price from the given fourteen independent variables.

In [18]:
```
# Loading Boston house Dataset
DF = pd.read_csv("..//Boston.csv")
# Display the first few rows of the dataset to inspect its structu
print("First 5 rows of the Boston House dataset:-\n", DF.head())
```

```
First 5 rows of the Boston House dataset:-
       crim    zn  indus  chas    nox     rm   age     dis  rad  t
ax  ptratio  \
0  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  29
6     15.3
1  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  24
2     17.8
2  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  24
2     17.8
3  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  22
2     18.7
4  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  22
2     18.7

    black  lstat  medv
0  396.90   4.98  24.0
1  396.90   9.14  21.6
2  392.83   4.03  34.7
3  394.63   2.94  33.4
4  396.90   5.33  36.2
```

Attribute Information

Input features in order:

1) CRIM: per capita crime rate by town

2) ZN: proportion of residential land zoned for lots over 25,000 sq.ft.

3) INDUS: proportion of non-retail business acres per town

4)CHAS: Charles River dummy variable (1 if tract bounds river; 0 otherwise)

5) NOX: nitric oxides concentration (parts per 10 million) [parts/10M]

6) RM: average number of rooms per dwelling

7) AGE: proportion of owner-occupied units built prior to 1940

8) DIS: weighted distances to five Boston employment centers

9) RAD: index of accessibility to radial highways

10) TAX: full-value property-tax rate per $10,000 [$/10k]

11) PTRATIO: pupil-teacher ratio by town

12) Black: The result of the equationB=1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
13) LSTAT: % lower status of the population

Output variable:
1) MEDV: Median value of owner-occupied homes in $1000's [k$]

Each record in the database describes a Boston suburb or town.

In [19]:
```
# Check the dimensions of the dataset (number of rows and columns)
print("Dimension of the dataset: ", DF.shape)
```

```
Dimension of the dataset:  (506, 14)
```

In [20]:
```
# information about the dataset
DF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   crim      506 non-null    float64
 1   zn        506 non-null    float64
 2   indus     506 non-null    float64
 3   chas      506 non-null    int64
 4   nox       506 non-null    float64
 5   rm        506 non-null    float64
 6   age       506 non-null    float64
 7   dis       506 non-null    float64
 8   rad       506 non-null    int64
 9   tax       506 non-null    int64
 10  ptratio   506 non-null    float64
 11  black     506 non-null    float64
 12  lstat     506 non-null    float64
 13  medv      506 non-null    float64
dtypes: float64(11), int64(3)
memory usage: 55.5 KB
```

In [21]:
```
# Extract features and target
attribute = DF.drop('medv', axis=1)
target = DF['medv']
```

In [22]:
```
# Split the data into training and testing sets
attribute_train, attribute_test, target_train, target_test = train
```

In [23]:
```
# Initialize and fit the StandardScaler
attribute_train_scaled = scaler.fit_transform(attribute_train)
attribute_test_scaled = scaler.transform(attribute_test)
```

In [24]:
```
from sklearn.linear_model import LinearRegression
# Initialize and train the Linear Regression model
model = LinearRegression()
model.fit(attribute_train_scaled, target_train)
```

Out[24]:
```
▾ LinearRegression
LinearRegression()
```

In [25]:
```
from sklearn.metrics import mean_squared_error
# Perform cross-validation
cv_predictions = model.predict(attribute_test_scaled)
cv_mse = mean_squared_error(target_test, cv_predictions)
print(f"Cross-Validation Mean Squared Error: {cv_mse:.4f}")
```

```
Cross-Validation Mean Squared Error: 24.2911
```

In [26]:
```
from sklearn.metrics import r2_score
# Calculate R-squared (Coefficient of Determination)
r2 = r2_score(target_test, cv_predictions)
print(f"R-squared: {r2:.4f}")
```

```
R-squared: 0.6688
```

In [27]:
```
# Create a DataFrame with actual and predicted values
results_DF = pd.DataFrame({
    'Actual Values': target_test.values,
    'Predicted Values': cv_predictions
})

results_DF.head(10)
```

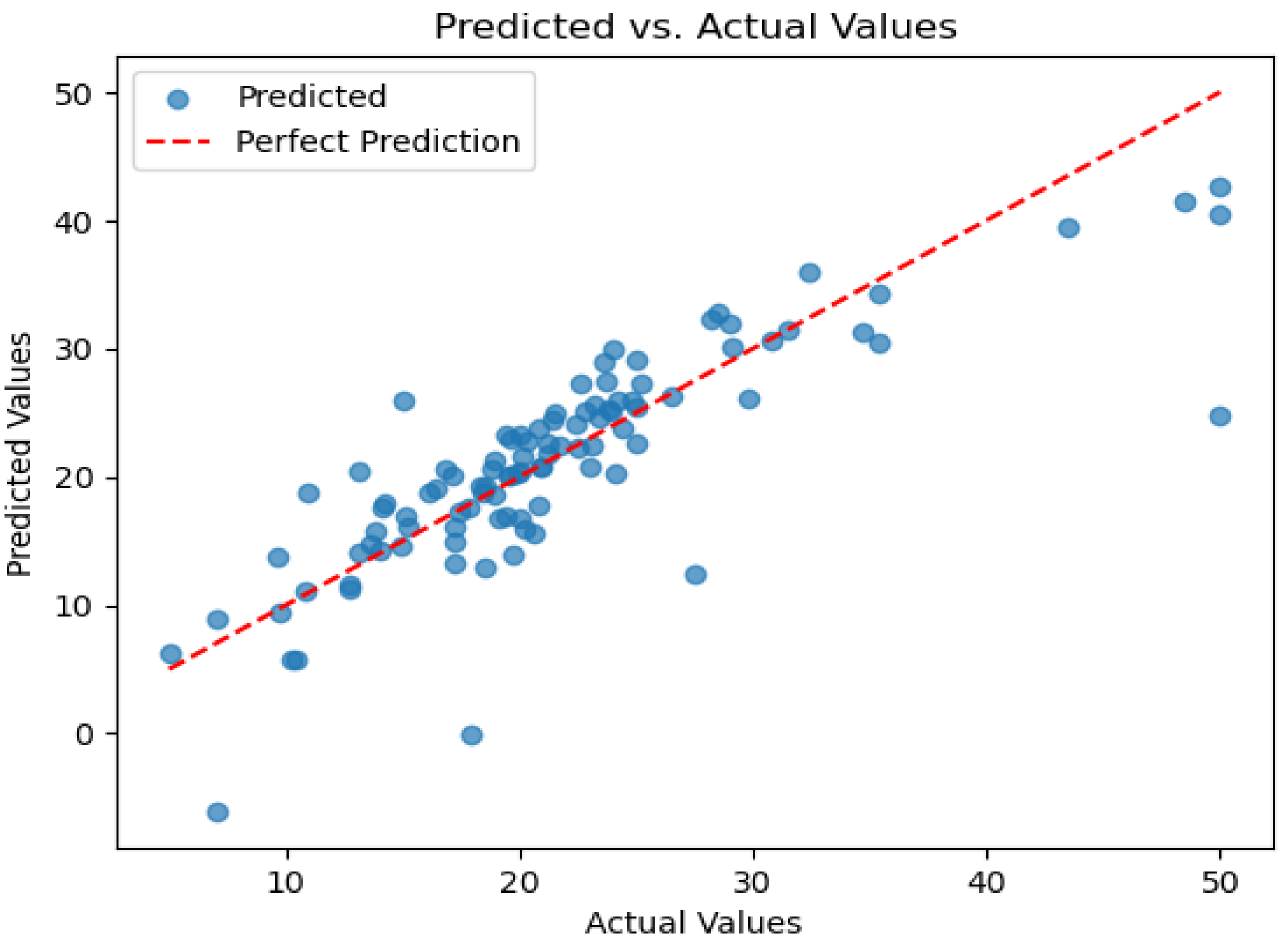
Out[27]:

	Actual Values	Predicted Values
0	23.6	28.996724
1	32.4	36.025565
2	13.6	14.816944
3	22.8	25.031979
4	16.1	18.769880
5	20.0	23.254429
6	17.8	17.662538
7	14.0	14.341190
8	19.6	23.013207
9	16.8	20.632456

Here the model's Predicted Values are almost matching with that of Actual Values. So, the model is not overfitting.

In [28]:

```
from matplotlib import pyplot as plt
# Plotting the linear regression line
plt.scatter(target_test, cv_predictions, alpha=0.7, label='Predict
plt.plot([min(target_test), max(target_test)], [min(target_test),
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Predicted vs. Actual Values')
plt.legend()
plt.show()
```



Here, the model is overestimating the actual values. i.e. the model is predicting higher values than what is actually observed. as most points are above the perfect prediction line(45-degree line). This could be due tothe model's simplicity or the data's noise.

In [29]:
```
import numpy as np
# Make predictions on unseen data
new_data = np.array([[0.02731, 18.0, 2.31, 0, 0.538, 6.575, 65.2,
new_data_scaled = scaler.transform(new_data)
predicted_value = model.predict(new_data_scaled)
print(f"Predicted Value: {predicted_value[0]:.2f}")
```

```
Predicted Value: 29.95
```

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