Homework 3 Report
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Homework Number: 3
Github Repository: https://github.com/vipravlipare/ECGR-5105-Intro-to-Machine-Learning

Problem 1

Source Code (1):

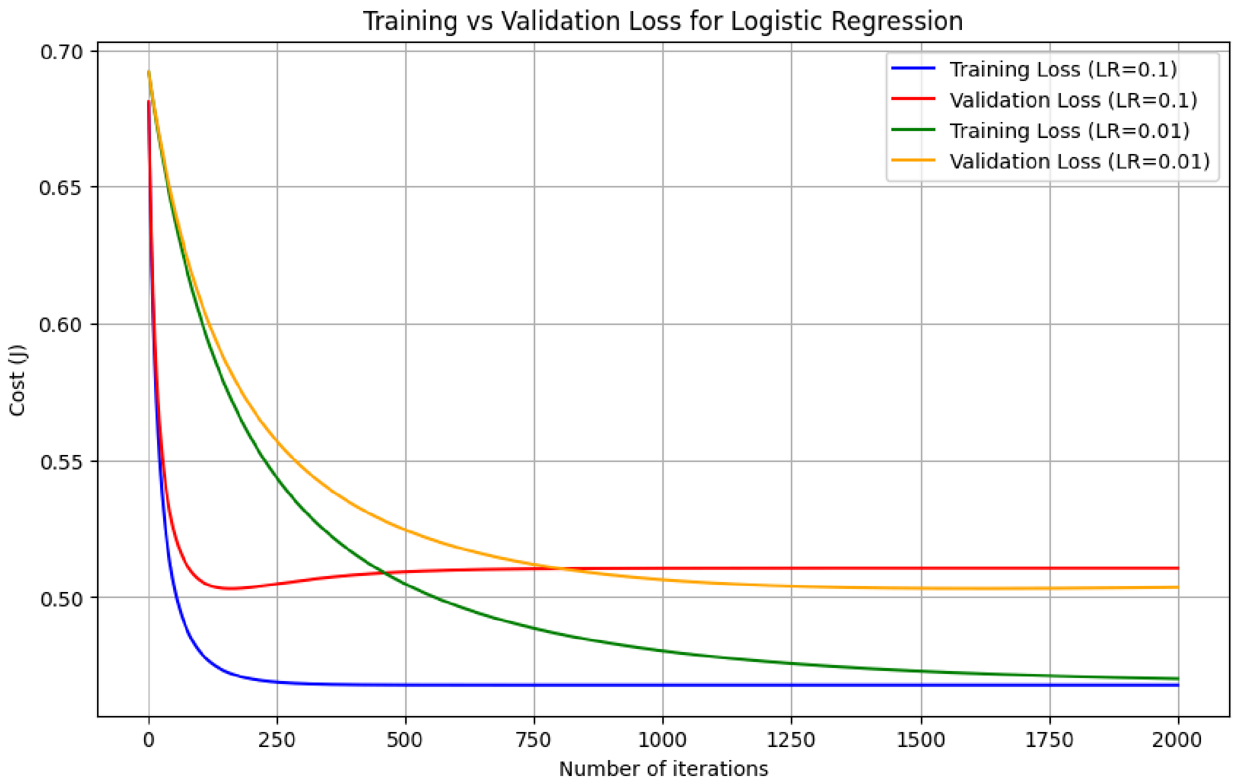
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score,
f1_score, confusion_matrix, ConfusionMatrixDisplay
file_path = "diabetes.csv"
sample = pd.read_csv(file_path)

m = len(Y)
X_0 = np.ones((m, 1))
X_cols = [sample['Pregnancies'].values.reshape(m,1),
          sample['Glucose'].values.reshape(m,1),
          sample['BloodPressure'].values.reshape(m,1),
          sample['SkinThickness'].values.reshape(m,1),
          sample['Insulin'].values.reshape(m,1),
          sample['BMI'].values.reshape(m,1),
          sample['DiabetesPedigreeFunction'].values.reshape(m,1),
          sample['Age'].values.reshape(m,1)]

X = np.hstack([X_0] + X_cols)
theta = np.zeros(X.shape[1])

# Split into train/test
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,
random_state=42)
scaler = StandardScaler()
X_train[:, 1:] = scaler.fit_transform(X_train[:, 1:])
X_test[:, 1:] = scaler.transform(X_test[:, 1:])

def sigmoid(z):
    return 1 / (1 + np.exp(-z))
```

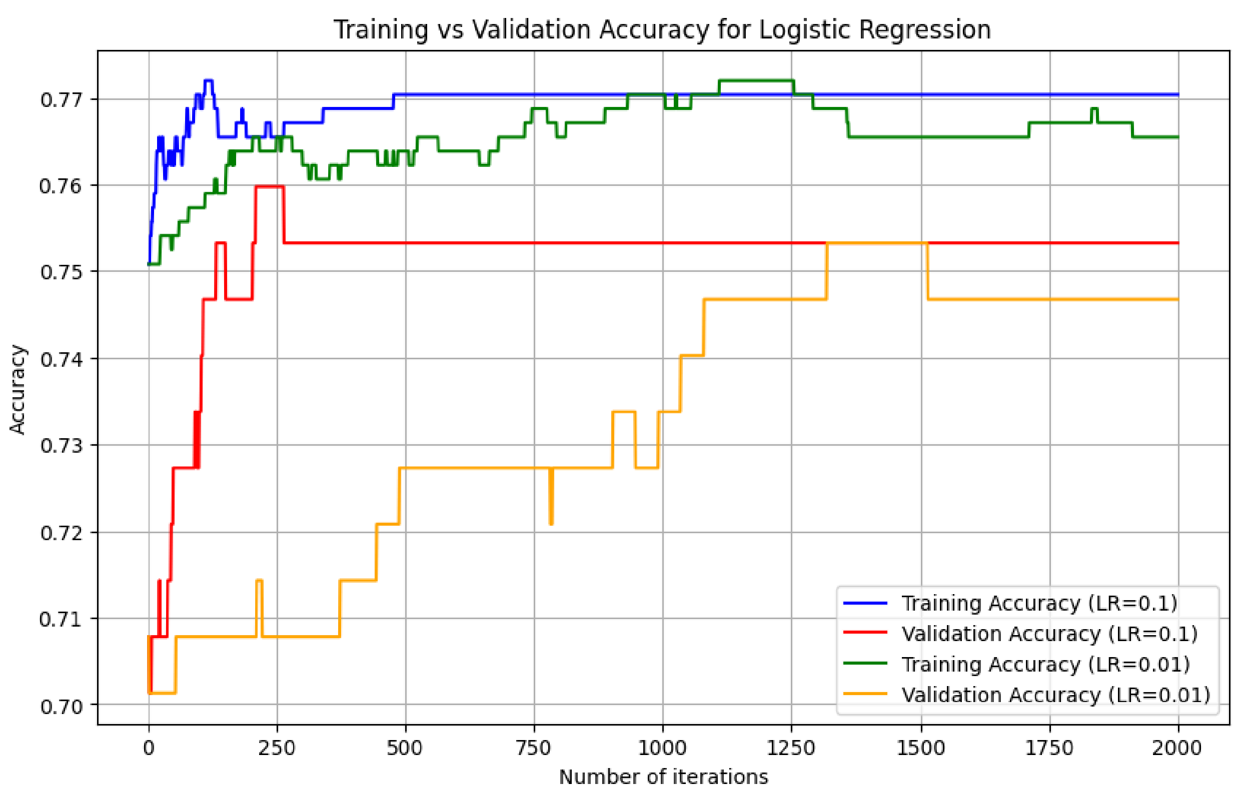
```
# defining function for computing the cost for linear regression
def compute_cost(X, y, theta):
    m = len(y)
    predictions = sigmoid(X.dot(theta))
    errors = predictions - y
    sqrErrors = np.square(errors)
    J = -(1/m) * np.sum(y * np.log(predictions) + (1 - y) * np.log(1 - 
predictions))
    return J

def compute_accuracy(X, y, theta):
    preds = (sigmoid(X.dot(theta)) >= 0.5).astype(int)
    return np.mean(preds == y)

# defining function for gradient descent algorithm
def gradient_descent(Xt, Yt, Xv, Yv, theta, alpha, iterations):
  train_cost_history = np.zeros(iterations)
  valid_cost_history = np.zeros(iterations)
  train_acc_history = np.zeros(iterations)
  valid_acc_history = np.zeros(iterations)
  m = len(Yt)
  for i in range(iterations):
    predictions = sigmoid(Xt.dot(theta))
    errors = np.subtract(predictions, Yt)
    sum_delta = (alpha / m) * Xt.transpose().dot(errors)
    theta = theta - sum_delta
    train_cost_history[i] = compute_cost(Xt, Yt, theta)
    valid_cost_history[i] = compute_cost(Xv, Yv, theta)
    train_acc_history[i] = compute_accuracy(Xt, Yt, theta)
    valid_acc_history[i] = compute_accuracy(Xv, Yv, theta)

  return theta, train_cost_history, valid_cost_history, train_acc_history, 
valid_acc_history


theta = np.zeros(X.shape[1])
iterations = 2000

alpha = 0.1
```

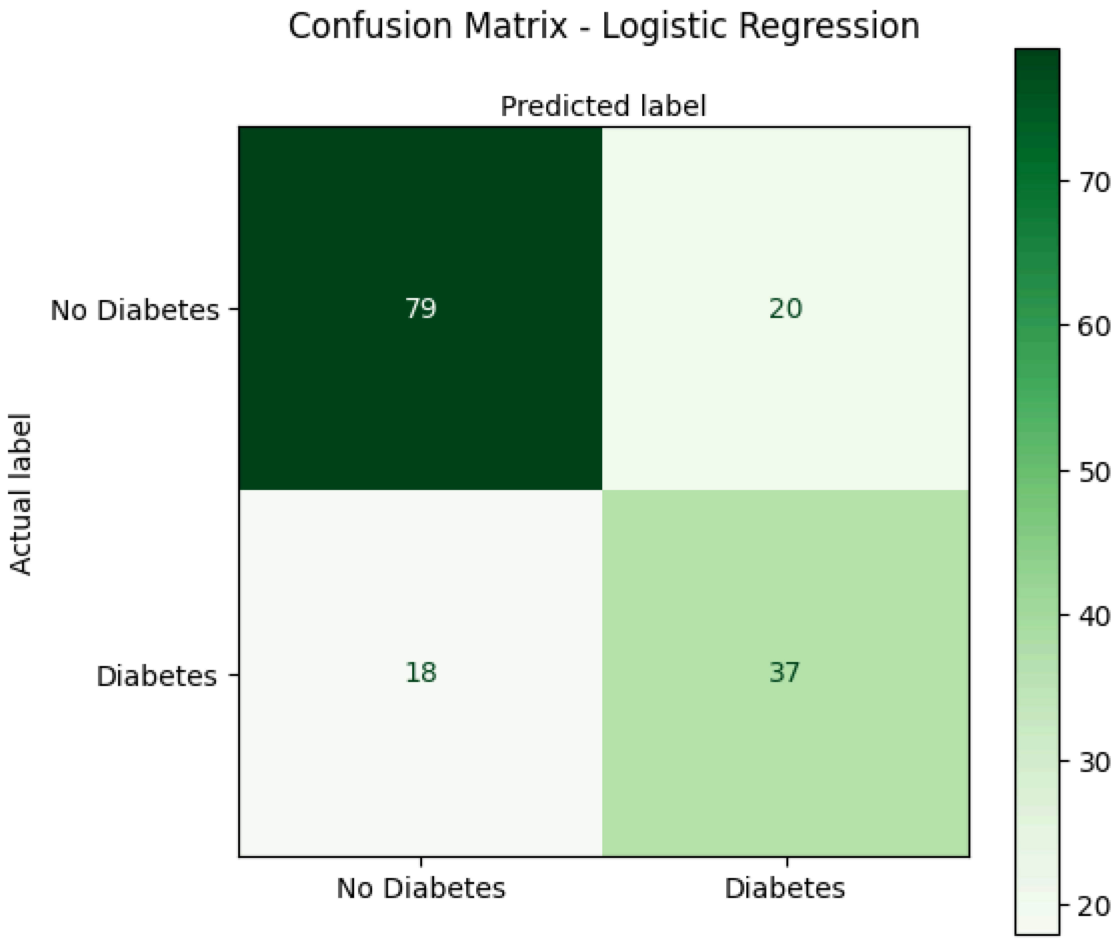
```
theta_1, train_cost_1, valid_cost_1, train_acc_1, valid_acc_1 =
gradient_descent(X_train, Y_train, X_test, Y_test, theta, alpha,
iterations)

alpha = 0.01
theta_2, train_cost_2, valid_cost_2, train_acc_2, valid_acc_2 =
gradient_descent(X_train, Y_train, X_test, Y_test, theta, alpha,
iterations)

plt.plot(range(1, iterations+1), train_cost_1, color='blue',
label='Training Loss (LR=0.1)')
plt.plot(range(1, iterations+1), valid_cost_1, color='red',
label='Validation Loss (LR=0.1)')
plt.plot(range(1, iterations+1), train_cost_2, color='green',
label='Training Loss (LR=0.01)')
plt.plot(range(1, iterations+1), valid_cost_2, color='orange',
label='Validation Loss (LR=0.01)')
plt.rcParams["figure.figsize"] = (10,6)
plt.grid()
plt.xlabel('Number of iterations')
plt.ylabel('Cost (J)')
plt.title('Training vs Validation Loss for Logistic Regression')
plt.legend()
plt.show()

plt.plot(range(1, iterations+1), train_acc_1, color='blue',
label='Training Accuracy (LR=0.1)')
plt.plot(range(1, iterations+1), valid_acc_1, color='red',
label='Validation Accuracy (LR=0.1)')
plt.plot(range(1, iterations+1), train_acc_2, color='green',
label='Training Accuracy (LR=0.01)')
plt.plot(range(1, iterations+1), valid_acc_2, color='orange',
label='Validation Accuracy (LR=0.01)')
plt.rcParams["figure.figsize"] = (10,6)
plt.grid()
plt.xlabel('Number of iterations')
plt.ylabel('Accuracy')
plt.title('Training vs Validation Accuracy for Logistic Regression')
plt.legend()
plt.show()
```

```python
Y_prob = sigmoid(X_test.dot(theta_1))
Y_pred = (Y_prob >= 0.5).astype(int)

accuracy = accuracy_score(Y_test, Y_pred)
precision = precision_score(Y_test, Y_pred)
recall = recall_score(Y_test, Y_pred)
f1 = f1_score(Y_test, Y_pred)

# Print performance results
print("Accuracy :" ,accuracy)
print("Precision:" ,precision)
print("Recall   :" ,recall)
print("F1 Score :" ,f1)

class_names = ["No Diabetes", "Diabetes"]
cm = confusion_matrix(Y_test, Y_pred)
fig, ax = plt.subplots(figsize=(6,5))
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
ax.xaxis.set_label_position("top")

# Plot confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=class_names)
disp.plot(cmap='Greens', ax=ax)
plt.tight_layout()
plt.title("Confusion Matrix - Logistic Regression", y=1.1)
plt.ylabel("Actual label")
plt.xlabel("Predicted label")
plt.show()
```

Figures / Results (1):







Accuracy : 0.7532467532467533
Precision: 0.6491228070175439
Recall   : 0.6727272727272727
F1 Score : 0.6607142857142857

Problem 2A

Source Code (2A):

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score,
f1_score, confusion_matrix, ConfusionMatrixDisplay
from sklearn import datasets
sample = datasets.load_breast_cancer()
X = sample.data
```

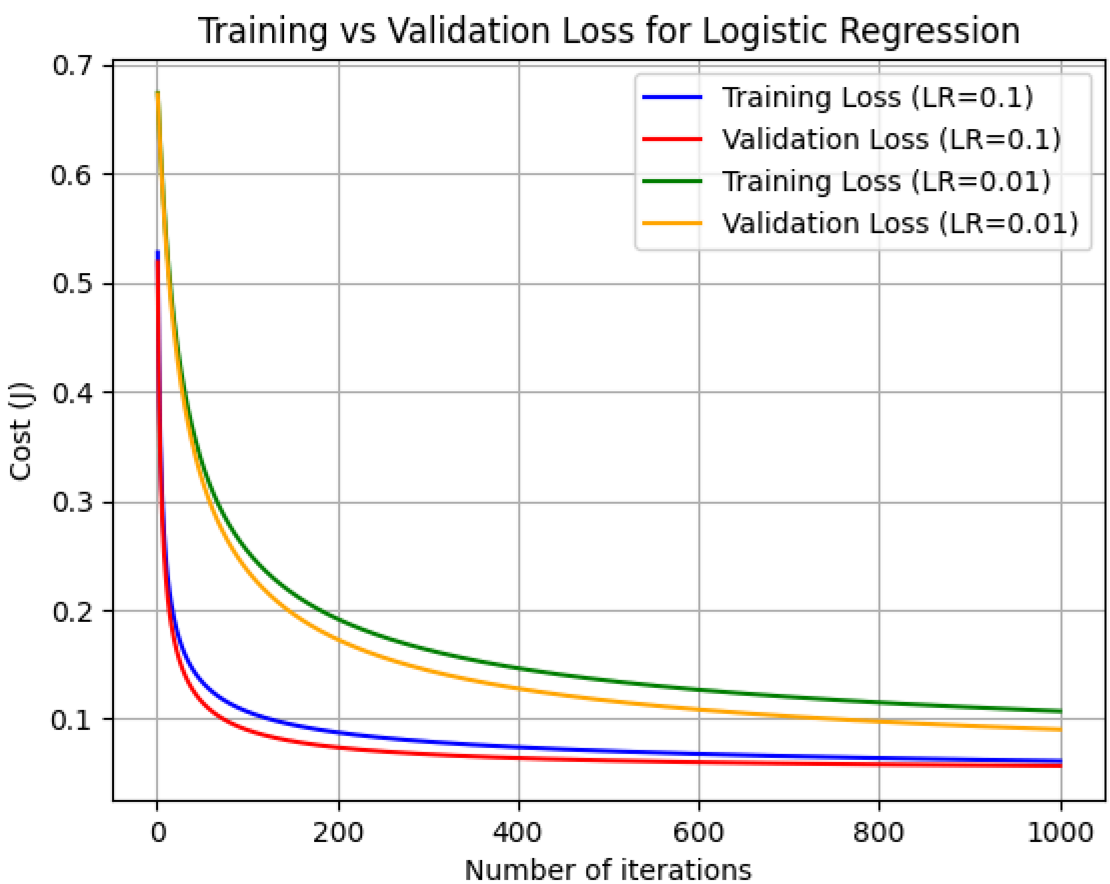
```
Y = sample.target

m = len(Y)
X_0 = np.ones((m, 1))
X = np.hstack([X_0, X])
theta = np.zeros(X.shape[1])

# Split into train/test
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,
random_state=42)
scaler = StandardScaler()
X_train[:, 1:] = scaler.fit_transform(X_train[:, 1:])
X_test[:, 1:] = scaler.transform(X_test[:, 1:])

def sigmoid(z):
    return 1 / (1 + np.exp(-z))

# defining function for computing the cost for linear regression
def compute_cost(X, y, theta):
    m = len(y)
    predictions = sigmoid(X.dot(theta))
    errors = predictions - y
    sqrErrors = np.square(errors)
    J = -(1/m) * np.sum(y * np.log(predictions) + (1 - y) * np.log(1 -
predictions))
    return J

def compute_accuracy(X, y, theta):
    preds = (sigmoid(X.dot(theta)) >= 0.5).astype(int)
    return np.mean(preds == y)

# defining function for gradient descent algorithm
# defining function for gradient descent algorithm
def gradient_descent(Xt, Yt, Xv, Yv, theta, alpha, iterations):
  train_cost_history = np.zeros(iterations)
  valid_cost_history = np.zeros(iterations)
  train_acc_history = np.zeros(iterations)
  valid_acc_history = np.zeros(iterations)
  m = len(Yt)
  for i in range(iterations):
```

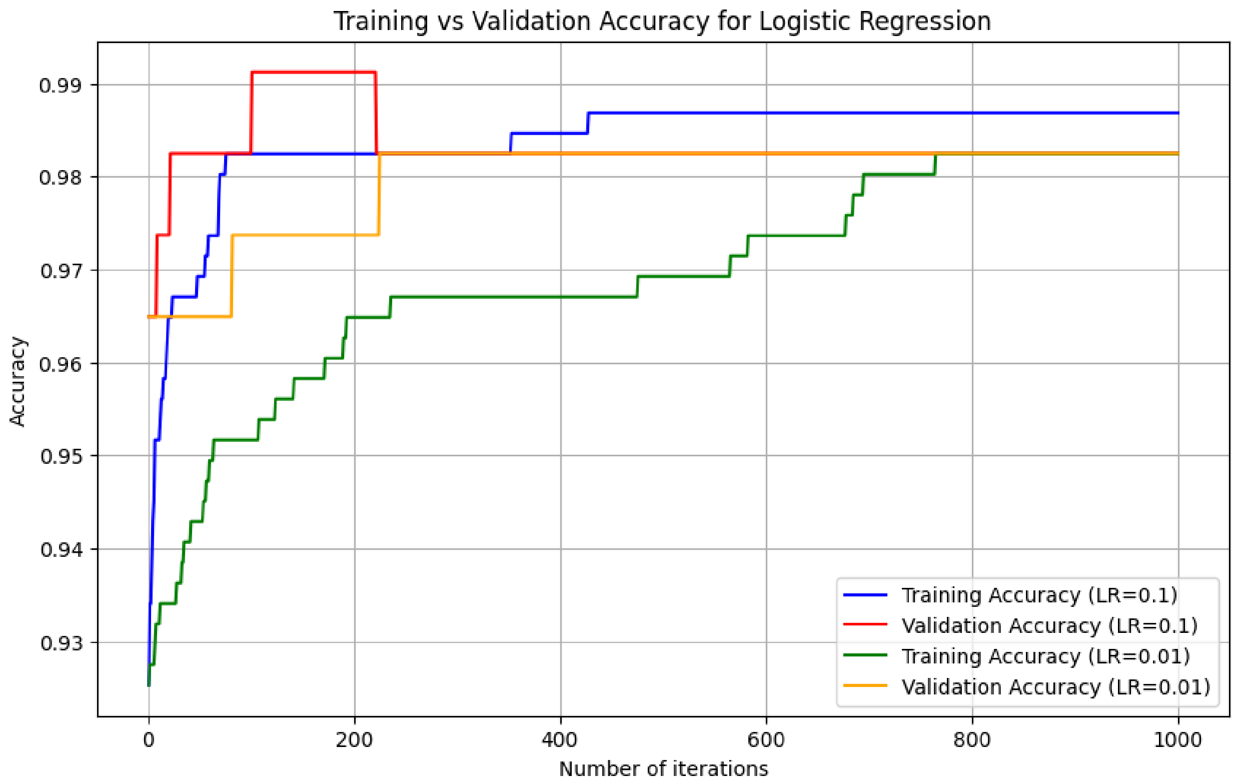
```
    predictions = sigmoid(Xt.dot(theta))
    errors = np.subtract(predictions, Yt)
    sum_delta = (alpha / m) * Xt.transpose().dot(errors)
    theta = theta - sum_delta
    train_cost_history[i] = compute_cost(Xt, Yt, theta)
    valid_cost_history[i] = compute_cost(Xv, Yv, theta)
    train_acc_history[i] = compute_accuracy(Xt, Yt, theta)
    valid_acc_history[i] = compute_accuracy(Xv, Yv, theta)

  return theta, train_cost_history, valid_cost_history, train_acc_history,
valid_acc_history

theta = np.zeros(X.shape[1])
iterations = 1000

alpha = 0.1
theta_1, train_cost_1, valid_cost_1, train_acc_1, valid_acc_1 =
gradient_descent(X_train, Y_train, X_test, Y_test, theta, alpha,
iterations)

alpha = 0.01
theta_2, train_cost_2, valid_cost_2, train_acc_2, valid_acc_2 =
gradient_descent(X_train, Y_train, X_test, Y_test, theta, alpha,
iterations)

plt.plot(range(1, iterations+1), train_cost_1, color='blue',
label='Training Loss (LR=0.1)')
plt.plot(range(1, iterations+1), valid_cost_1, color='red',
label='Validation Loss (LR=0.1)')
plt.plot(range(1, iterations+1), train_cost_2, color='green',
label='Training Loss (LR=0.01)')
plt.plot(range(1, iterations+1), valid_cost_2, color='orange',
label='Validation Loss (LR=0.01)')
plt.rcParams["figure.figsize"] = (10,6)
plt.grid()
plt.xlabel('Number of iterations')
plt.ylabel('Cost (J)')
plt.title('Training vs Validation Loss for Logistic Regression')
plt.legend()
plt.show()
```

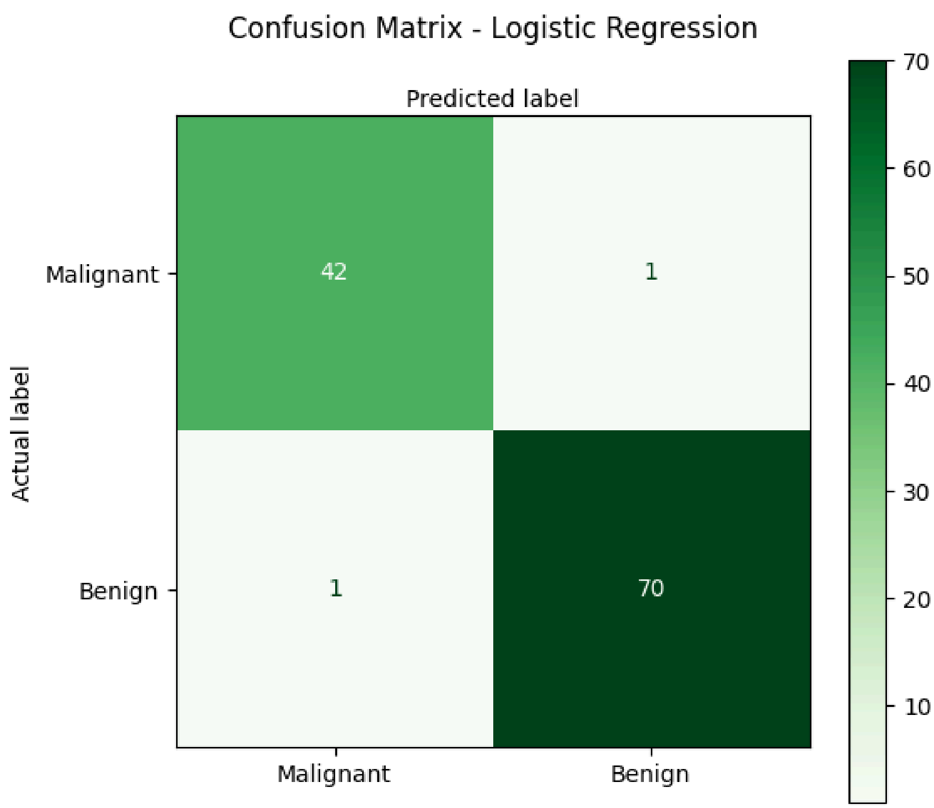
```python
plt.plot(range(1, iterations+1), train_acc_1, color='blue',
label='Training Accuracy (LR=0.1)')
plt.plot(range(1, iterations+1), valid_acc_1, color='red',
label='Validation Accuracy (LR=0.1)')
plt.plot(range(1, iterations+1), train_acc_2, color='green',
label='Training Accuracy (LR=0.01)')
plt.plot(range(1, iterations+1), valid_acc_2, color='orange',
label='Validation Accuracy (LR=0.01)')
plt.rcParams["figure.figsize"] = (10,6)
plt.grid()
plt.xlabel('Number of iterations')
plt.ylabel('Accuracy')
plt.title('Training vs Validation Accuracy for Logistic Regression')
plt.legend()
plt.show()

Y_prob = sigmoid(X_test.dot(theta_1))
Y_pred = (Y_prob >= 0.5).astype(int)

accuracy = accuracy_score(Y_test, Y_pred)
precision = precision_score(Y_test, Y_pred)
recall = recall_score(Y_test, Y_pred)
f1 = f1_score(Y_test, Y_pred)

# Print performance results
print("Accuracy :" ,accuracy)
print("Precision:" ,precision)
print("Recall   :" ,recall)
print("F1 Score :" ,f1)

class_names = ["Malignant", "Benign"]
cm = confusion_matrix(Y_test, Y_pred)
fig, ax = plt.subplots(figsize=(6,5))

# Set ticks manually
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
ax.xaxis.set_label_position("top")
```

```
# Plot confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=class_names)
disp.plot(cmap='Greens', ax=ax)

plt.tight_layout()
plt.title("Confusion Matrix - Logistic Regression", y=1.1)
plt.ylabel("Actual label")
plt.xlabel("Predicted label")
plt.show()
```

Figures / Results (2A):







Accuracy : 0.9824561403508771
Precision: 0.9859154929577465

Recall   : 0.9859154929577465
F1 Score : 0.9859154929577465

Problem 2B
<u>Source Code</u> (2B):

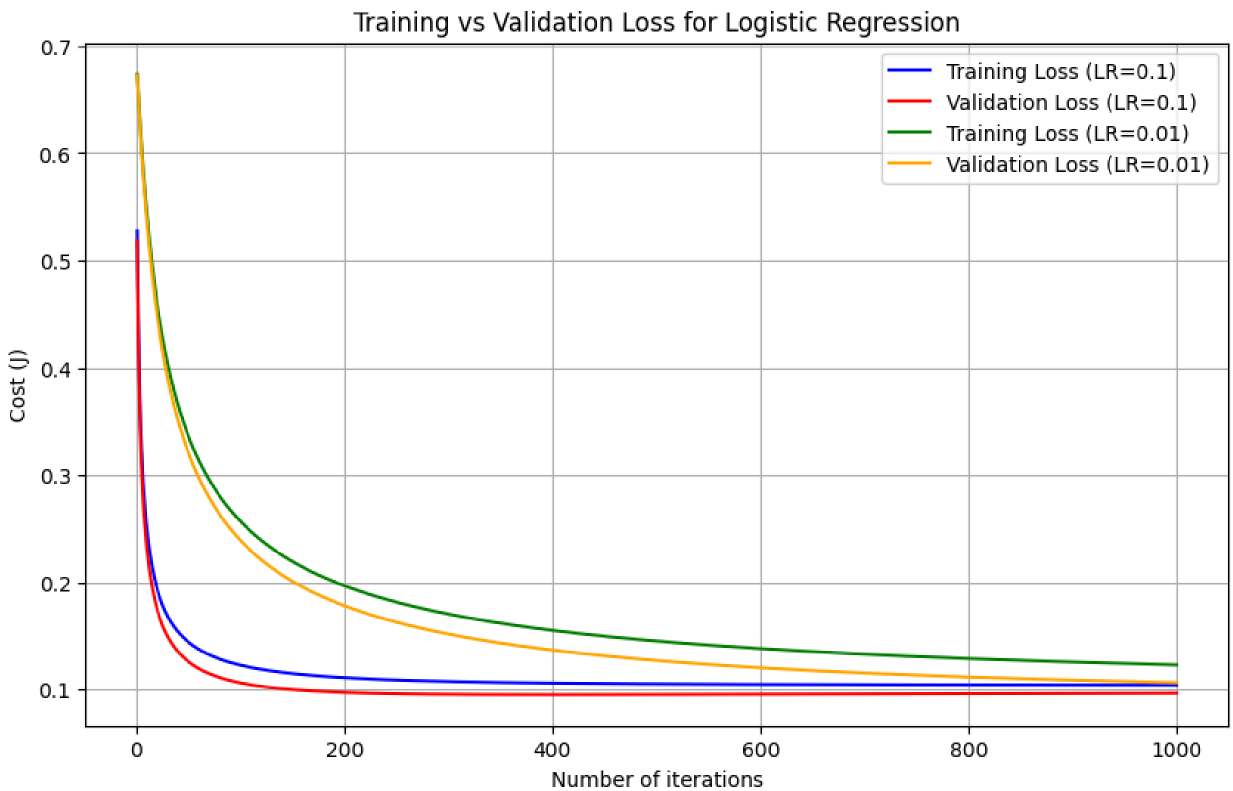
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score,
f1_score, confusion_matrix, ConfusionMatrixDisplay
from sklearn import datasets
sample = datasets.load_breast_cancer()  # Use breast cancer dataset from
sklearn
X = sample.data
Y = sample.target

m = len(Y)
X_0 = np.ones((m, 1))
X = np.hstack([X_0, X])
theta = np.zeros(X.shape[1])

# Split into train/test
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2,
random_state=42)
scaler = StandardScaler()
X_train[:, 1:] = scaler.fit_transform(X_train[:, 1:])
X_test[:, 1:] = scaler.transform(X_test[:, 1:])

def sigmoid(z):
    return 1 / (1 + np.exp(-z))

# defining function for computing the cost for linear regression
def compute_cost(X, y, theta):
    m = len(y)
    predictions = sigmoid(X.dot(theta))
    errors = predictions - y
    sqrErrors = np.square(errors)
```

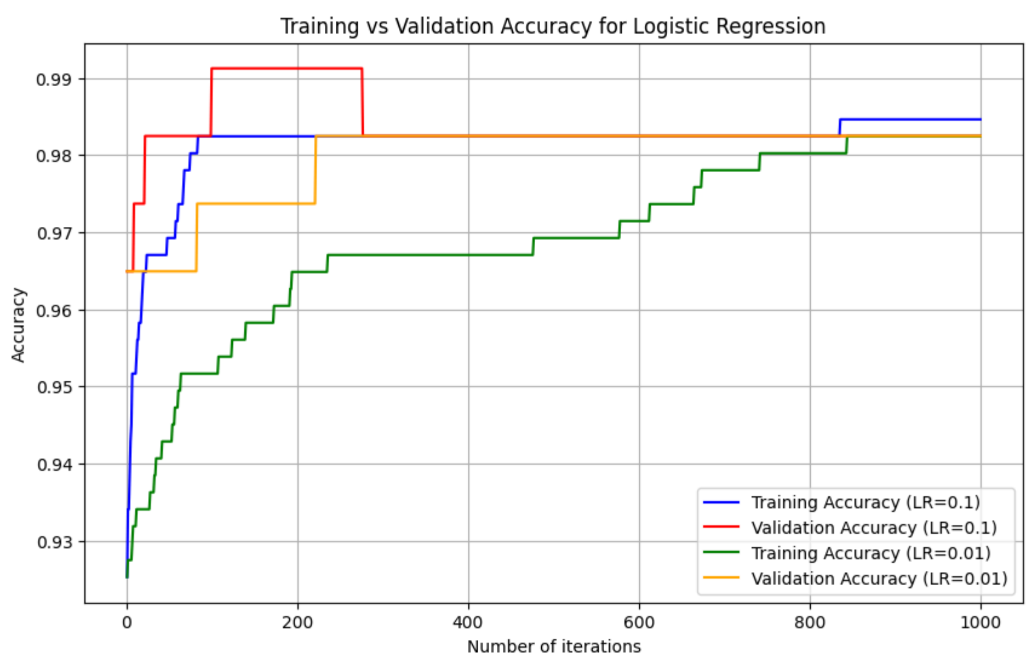
```
    J = -(1/m) * np.sum(y * np.log(predictions) + (1 - y) * np.log(1 -
predictions))
    return J

def compute_accuracy(X, y, theta):
    preds = (sigmoid(X.dot(theta)) >= 0.5).astype(int)
    return np.mean(preds == y)

# defining function for gradient descent algorithm
def gradient_descent(Xt, Yt, Xv, Yv, theta, alpha, iterations, lam):
  train_cost_history = np.zeros(iterations)
  valid_cost_history = np.zeros(iterations)
  train_acc_history = np.zeros(iterations)
  valid_acc_history = np.zeros(iterations)
  m = len(Yt)
  for i in range(iterations):
    predictions = sigmoid(Xt.dot(theta))
    errors = np.subtract(predictions, Yt)
    sum_delta = (alpha / m) * Xt.transpose().dot(errors)
    sum_delta[1:] += (alpha * lam / m) * theta[1:]
    theta = theta - sum_delta
    # Compute cost including L2 penalty
    train_cost_history[i] = compute_cost(Xt, Yt, theta) + (lam/(2*m)) *
np.sum(theta[1:]**2)
    valid_cost_history[i] = compute_cost(Xv, Yv, theta) + (lam/(2*m)) *
np.sum(theta[1:]**2)
    train_acc_history[i] = compute_accuracy(Xt, Yt, theta)
    valid_acc_history[i] = compute_accuracy(Xv, Yv, theta)

  return theta, train_cost_history, valid_cost_history, train_acc_history,
valid_acc_history

theta = np.zeros(X.shape[1])
iterations = 1000
lam = 5

alpha = 0.1
theta_1, train_cost_1, valid_cost_1, train_acc_1, valid_acc_1 =
gradient_descent(X_train, Y_train, X_test, Y_test, theta, alpha,
iterations, lam)
```

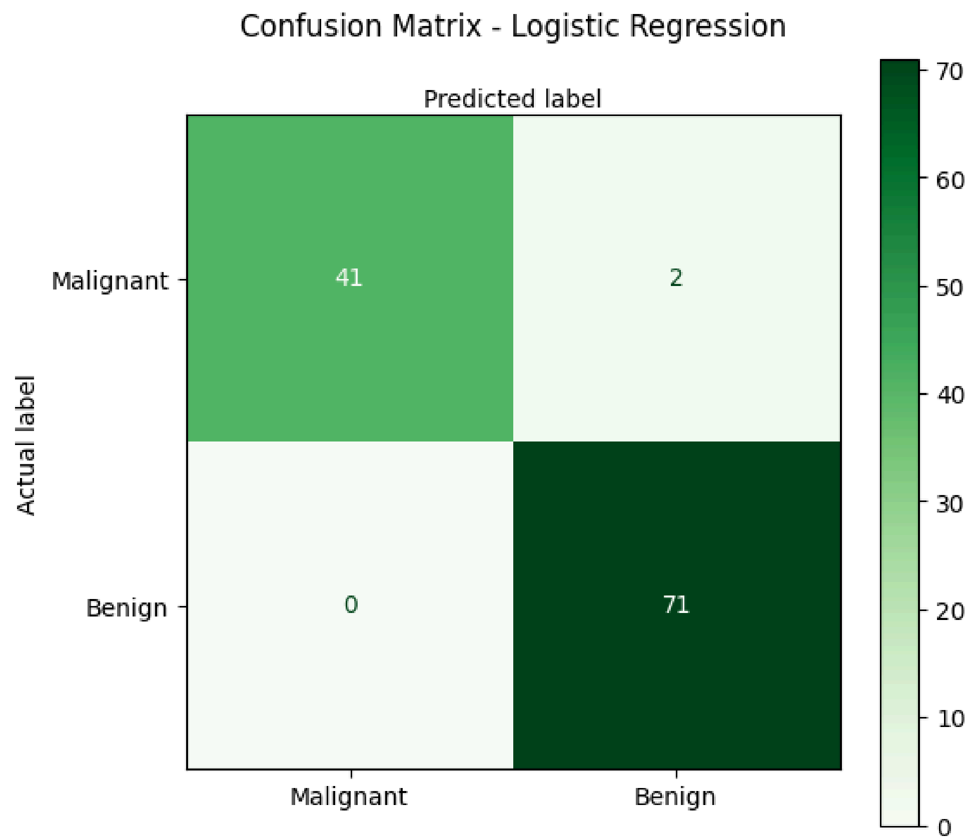
```
alpha = 0.01
theta_2, train_cost_2, valid_cost_2, train_acc_2, valid_acc_2 =
gradient_descent(X_train, Y_train, X_test, Y_test, theta, alpha,
iterations, lam)

plt.plot(range(1, iterations+1), train_cost_1, color='blue',
label='Training Loss (LR=0.1)')
plt.plot(range(1, iterations+1), valid_cost_1, color='red',
label='Validation Loss (LR=0.1)')
plt.plot(range(1, iterations+1), train_cost_2, color='green',
label='Training Loss (LR=0.01)')
plt.plot(range(1, iterations+1), valid_cost_2, color='orange',
label='Validation Loss (LR=0.01)')
plt.rcParams["figure.figsize"] = (10,6)
plt.grid()
plt.xlabel('Number of iterations')
plt.ylabel('Cost (J)')
plt.title('Training vs Validation Loss for Logistic Regression')
plt.legend()
plt.show()

plt.plot(range(1, iterations+1), train_acc_1, color='blue',
label='Training Accuracy (LR=0.1)')
plt.plot(range(1, iterations+1), valid_acc_1, color='red',
label='Validation Accuracy (LR=0.1)')
plt.plot(range(1, iterations+1), train_acc_2, color='green',
label='Training Accuracy (LR=0.01)')
plt.plot(range(1, iterations+1), valid_acc_2, color='orange',
label='Validation Accuracy (LR=0.01)')
plt.rcParams["figure.figsize"] = (10,6)
plt.grid()
plt.xlabel('Number of iterations')
plt.ylabel('Accuracy')
plt.title('Training vs Validation Accuracy for Logistic Regression')
plt.legend()
plt.show()

Y_prob = sigmoid(X_test.dot(theta_1))
Y_pred = (Y_prob >= 0.5).astype(int)
```

```python
accuracy = accuracy_score(Y_test, Y_pred)
precision = precision_score(Y_test, Y_pred)
recall = recall_score(Y_test, Y_pred)
f1 = f1_score(Y_test, Y_pred)

# Print performance results
print("Accuracy :" ,accuracy)
print("Precision:" ,precision)
print("Recall    :" ,recall)
print("F1 Score :" ,f1)

class_names = ["Malignant", "Benign"]
cm = confusion_matrix(Y_test, Y_pred)
fig, ax = plt.subplots(figsize=(6,5))

# Set ticks manually
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
ax.xaxis.set_label_position("top")

# Plot confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=class_names)
disp.plot(cmap='Greens', ax=ax)

plt.tight_layout()
plt.title("Confusion Matrix - Logistic Regression", y=1.1)
plt.ylabel("Actual label")
plt.xlabel("Predicted label")
plt.show()
```

Figures / Results (2B):







Accuracy : 0.9824561403508771
Precision: 0.9726027397260274
Recall : 1.0
F1 Score : 0.9861111111111112