Assignment3

July 10, 2025

[1]:
```
# Importing Libraries
import warnings
warnings.filterwarnings('ignore')

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import KFold, cross_val_score, train_test_split
from sklearn.linear_model import LogisticRegression, LogisticRegressionCV
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.preprocessing import StandardScaler
from sklearn import metrics
import seaborn as sns
```

[2]:
```
# Model Training Function
def model_training(X_train, y_train, X_test, y_test, cv=None, penalty=None, C=0.
↪1, solver='lbfgs'):
    classifier = LogisticRegression(penalty=penalty, C=C, solver=solver,␣
↪random_state=0)
    classifier.fit(X_train, y_train)
    y_pred = classifier.predict(X_test)
    cnf_matrix = confusion_matrix(y_test, y_pred)
    return cnf_matrix, y_pred
```

[3]:
```
# Confusion Matrix Plotting Function
def get_confusion_matrix(cnf_matrix):
    class_names = [0, 1]  # number of classes
    fig, ax = plt.subplots()
    tick_marks = np.arange(len(class_names))
    plt.xticks(tick_marks, class_names)
    plt.yticks(tick_marks, class_names)

    # create heatmap
    sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu", fmt='g')
    ax.xaxis.set_label_position("top")
    plt.tight_layout()
    plt.title('Confusion matrix', y=1.1)
```

```
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')
```

0.1 Diabetes Dataset

[5]:
```
# Read and Display the Diabetes Dataset
df = pd.read_csv("/content/diabetes.csv")
print("CSV File Shape")
print(df.shape)
df.head()
```

```
CSV File Shape
(768, 9)
```

[5]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1
```

[6]:
```
# Splitting Features and Labels
X = df.iloc[:, :-1].values   # All columns except the last one (features)
Y = df.iloc[:, -1].values    # Last column (target)
```

[7]:
```
# Standardizing the Features
sc_X = StandardScaler()
X_scaled = sc_X.fit_transform(X)
```

[8]:
```
# Splitting into Training and Testing Sets
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.20,␣
 ↪random_state=42)
```

Problem 1:

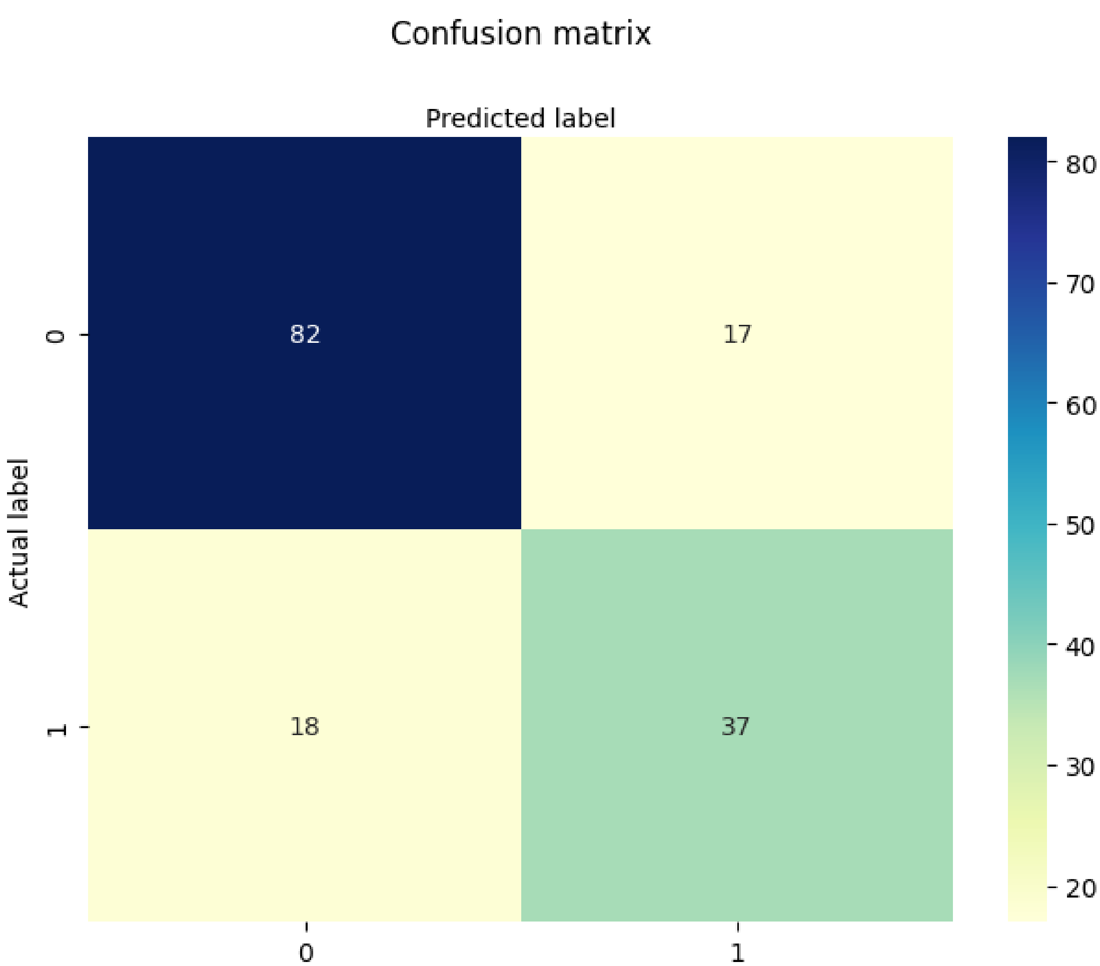
[9]:
```
# Train & Evaluate Logistic Regression Model
cnf_matrix, Y_pred = model_training(X_train, y_train, X_test, y_test,␣
 ↪penalty=None)
```

[10]:
```python
def get_results(y_test, y_pred):
    acc = metrics.accuracy_score(y_test, y_pred)
    print("Accuracy:", metrics.accuracy_score(y_test, y_pred))
    print("Precision:", metrics.precision_score(y_test, y_pred))
    print("Recall:", metrics.recall_score(y_test, y_pred))
    print("F1-score:", metrics.f1_score(y_test, y_pred))
    return acc * 100

# Print Evaluation Metrics
acc_1 = get_results(y_test, Y_pred)
```

```
Accuracy: 0.7727272727272727
Precision: 0.6851851851851852
Recall: 0.6727272727272727
F1-score: 0.6788990825688074
```

[11]:
```python
# Display Confusion Matrix
get_confusion_matrix(cnf_matrix)
```



Cancer Dataset

[12]:
```
import pandas as pd

# Load CSV file
df = pd.read_csv("/content/cancer.csv")
print("CSV Shape:", df.shape)
df.head()
```

```
CSV Shape: (569, 33)
```

[12]:
```
         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 points_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

   …  texture_worst  perimeter_worst  area_worst  smoothness_worst  \
0  …          17.33           184.60      2019.0            0.1622
1  …          23.41           158.80      1956.0            0.1238
2  …          25.53           152.50      1709.0            0.1444
3  …          26.50            98.87       567.7            0.2098
4  …          16.67           152.20      1575.0            0.1374

   compactness_worst  concavity_worst  concave points_worst  symmetry_worst  \
0             0.6656           0.7119                0.2654          0.4601
1             0.1866           0.2416                0.1860          0.2750
2             0.4245           0.4504                0.2430          0.3613
3             0.8663           0.6869                0.2575          0.6638
4             0.2050           0.4000                0.1625          0.2364

   fractal_dimension_worst  Unnamed: 32
0                  0.11890          NaN
1                  0.08902          NaN
2                  0.08758          NaN
3                  0.17300          NaN
4                  0.07678          NaN
```

```
[5 rows x 33 columns]
```

[13]:
```python
# Drop non-numeric 'id' and 'diagnosis' from features
X = df.drop(['id', 'diagnosis'], axis=1).values

# Encode 'diagnosis' (M = 1, B = 0)
Y = df['diagnosis'].map({'M': 1, 'B': 0}).values
```

[14]:
```python
# Impute missing values
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='mean')
X = imputer.fit_transform(X)
```

[15]:
```python
# Split and Scale the Data
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.20,␣
↪random_state=42)

sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
```

Problem 2.1

[16]:
```python
# Train logistic regression
from sklearn.linear_model import LogisticRegression

model = LogisticRegression(penalty='l2', solver='lbfgs', max_iter=1000)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

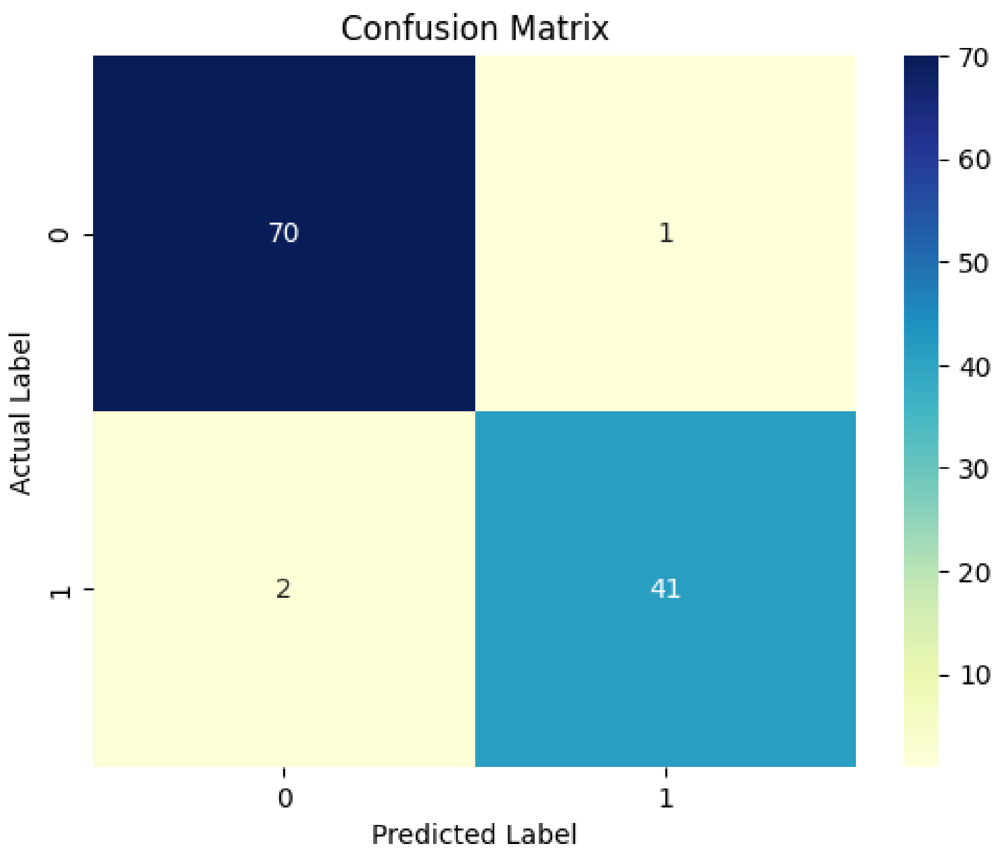
[19]:
```python
# Evaluate the Model
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score

# Print metrics
acc = accuracy_score(y_test, y_pred)
prec = precision_score(y_test, y_pred)
rec = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print("Accuracy:", acc)
print("Precision:", prec)
print("Recall:", rec)
print("F1-Score:", f1)
```

```
Accuracy: 0.9736842105263158
Precision: 0.9761904761904762
Recall: 0.9534883720930233
F1-Score: 0.9647058823529412
```

[18]:
```python
# Plot Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(pd.DataFrame(cm), annot=True, fmt='g', cmap='YlGnBu')
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("Actual Label")
plt.show()
```

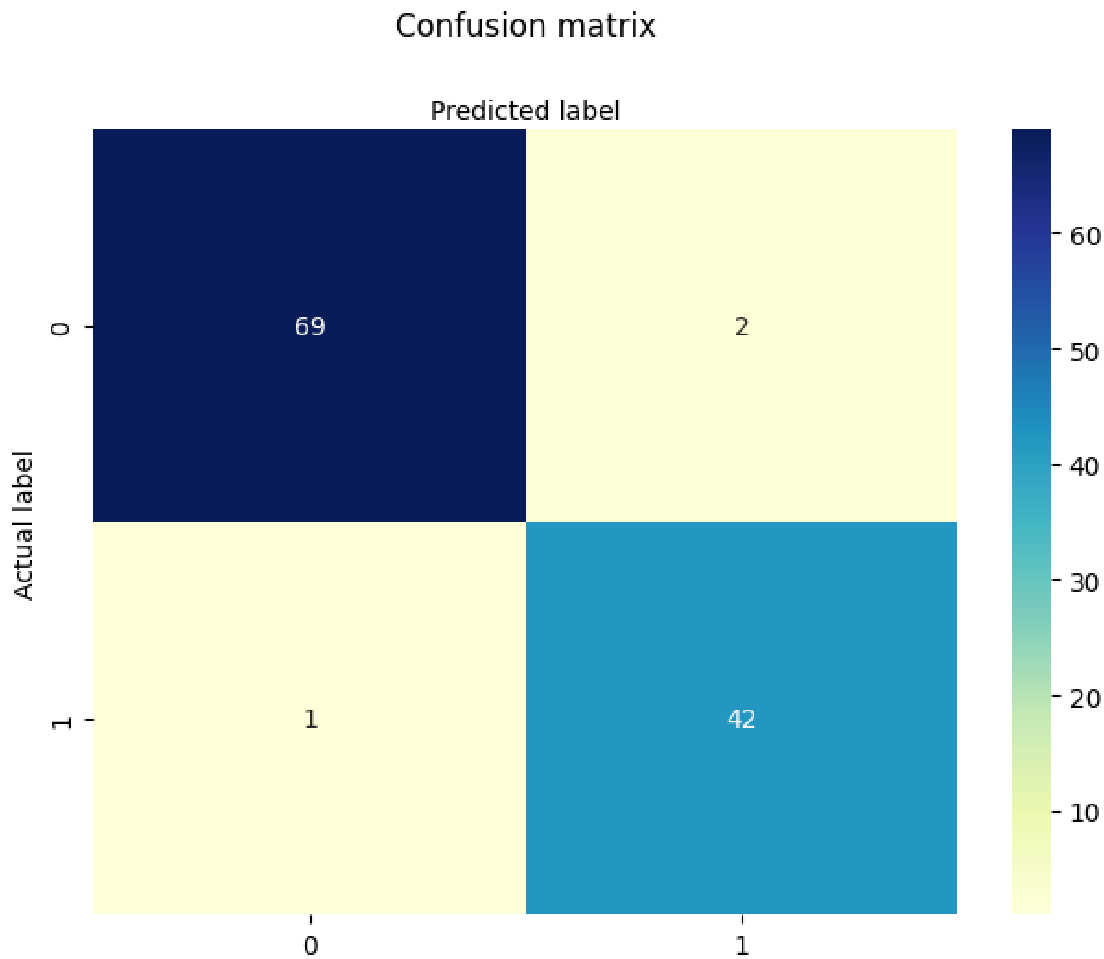


Problem 2.2

[20]:
```python
# Add the weight penalty and repeat the training
cnf_matrix_2_b, y_pred_2_b = model_training(
    X_train, y_train, X_test, y_test,
    penalty='l2', C=10, solver='lbfgs'
)
```

[21]:
```
# Plot Confusion Matrix
acc_2_b = get_results(y_test, y_pred_2_b)
get_confusion_matrix(cnf_matrix_2_b)
```

```
Accuracy: 0.9736842105263158
Precision: 0.9545454545454546
Recall: 0.9767441860465116
F1-score: 0.9655172413793104
```



Problem 3:

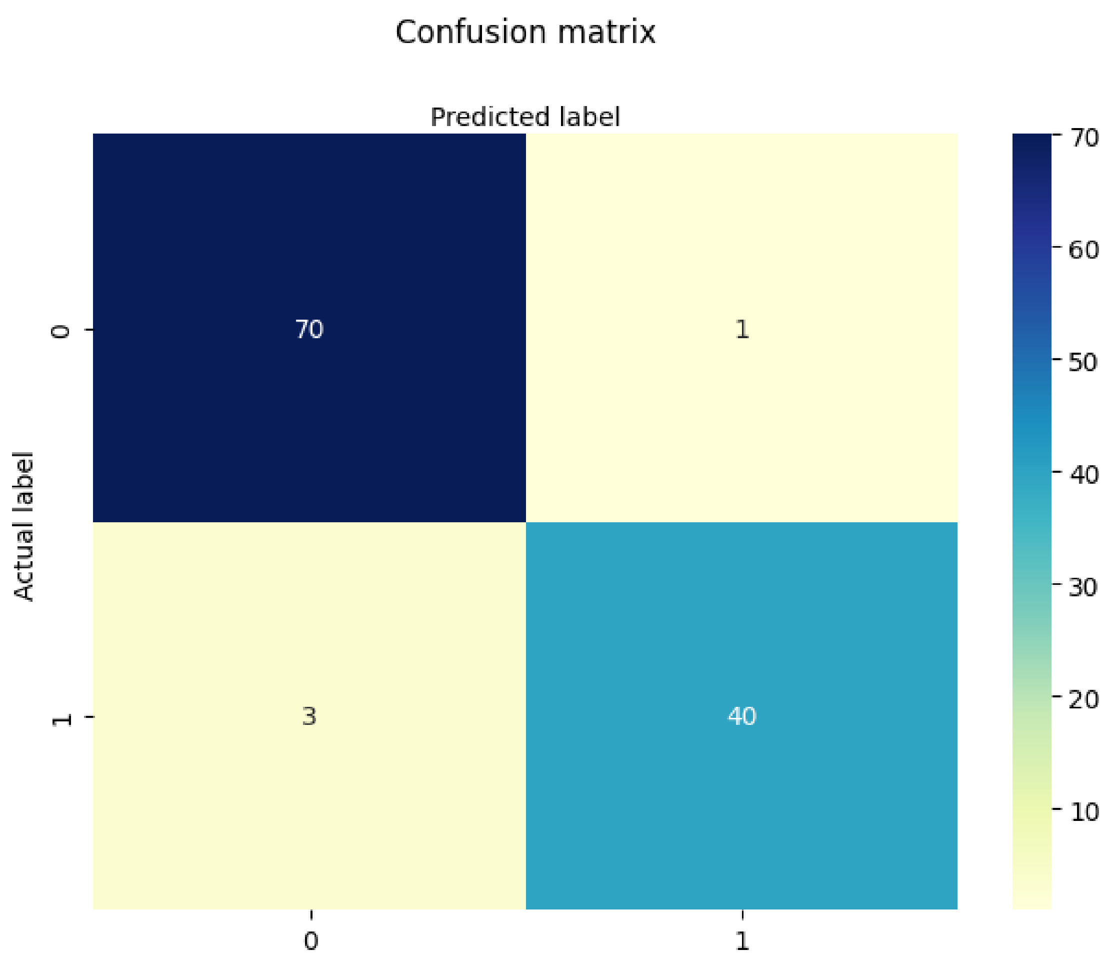
[22]:
```
# Model Training
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix

def model_training_NB(X_train, y_train, X_test, y_test):
    classifier = GaussianNB()
```

```
    y_pred = classifier.fit(X_train, y_train).predict(X_test)
    cnf_matrix = confusion_matrix(y_test, y_pred)
    return cnf_matrix, y_pred
```

[23]:
```
# Train and evaluate the model
cnf_matrix_3, y_pred_3 = model_training_NB(X_train, y_train, X_test, y_test)
acc_3 = get_results(y_test, y_pred_3)
get_confusion_matrix(cnf_matrix_3)
```

```
Accuracy: 0.9649122807017544
Precision: 0.975609756097561
Recall: 0.9302325581395349
F1-score: 0.9523809523809523
```



Problem 4 & 5:

[24]:
```
# PCA + Classification
from sklearn.decomposition import PCA
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score

def get_results(y_test, y_pred):
    acc = accuracy_score(y_test, y_pred)
    pre = precision_score(y_test, y_pred)
    rec = recall_score(y_test, y_pred)
    fscore = f1_score(y_test, y_pred)
    print("Accuracy:", acc)
    print("Precision:", pre)
    print("Recall:", rec)
    print("F1-Score:", fscore)
    return [acc*100.0, pre*100.0, rec*100.0, fscore*100.0]
```

[25]:
```
# Logistic Regression with PCA
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

def logist_model_training_pca(X, Y):
    n = X.shape[1]
    acc_list = []
    recall_list = []
    precision_list = []
    f1score_list = []
    k_list = []

    for i in range(n):
        print("K = " + str(i+1))
        pca = PCA(n_components=i+1)
        principalComponents = pca.fit_transform(X)
        X_train, X_test, y_train, y_test =␣
↪train_test_split(principalComponents, Y, test_size=0.20, random_state=9999)

        classifier = LogisticRegression(random_state=9)
        y_pred = classifier.fit(X_train, y_train).predict(X_test)

        re = get_results(y_test, y_pred)
        acc_list.append(re[0])
        precision_list.append(re[1])
        recall_list.append(re[2])
        f1score_list.append(re[3])
        k_list.append(i+1)

    high_acc = max(acc_list)
    high_acc_k = acc_list.index(high_acc) + 1
```

```
    print("------------------------------")
    print("Highest Classification Accuracy Achieved: " + str(high_acc) + " for␣
 ↪K number = " + str(high_acc_k))
    return k_list, acc_list, precision_list, recall_list, f1score_list
```

[26]:

```
# Naive Bayes with PCA
from sklearn.naive_bayes import GaussianNB

def GaussianNB_model_training_pca(X, Y):
    n = X.shape[1]
    acc_list = []
    recall_list = []
    precision_list = []
    f1score_list = []
    k_list = []

    for i in range(n):
        print("K = " + str(i+1))
        pca = PCA(n_components=i+1)
        principalComponents = pca.fit_transform(X)
        X_train, X_test, y_train, y_test =␣
 ↪train_test_split(principalComponents, Y, test_size=0.20, random_state=9999)

        classifier = GaussianNB()
        y_pred = classifier.fit(X_train, y_train).predict(X_test)

        re = get_results(y_test, y_pred)
        acc_list.append(re[0])
        precision_list.append(re[1])
        recall_list.append(re[2])
        f1score_list.append(re[3])
        k_list.append(i+1)

    high_acc = max(acc_list)
    high_acc_k = acc_list.index(high_acc) + 1
    print("------------------------------")
    print("Highest Classification Accuracy Achieved: " + str(high_acc) + " for␣
 ↪K number = " + str(high_acc_k))
    return k_list, acc_list, precision_list, recall_list, f1score_list
```

[27]:

```
# Plotting the Results
import matplotlib.pyplot as plt

def plot_result_with_k(k_list, acc_list, precision_list, recall_list,␣
 ↪f1score_list):
    plt.plot(k_list, acc_list, label = "Accuracy")
    plt.plot(k_list, precision_list, label = "Precision")
```

```
    plt.plot(k_list, recall_list, label = "Recall")
    plt.plot(k_list, f1score_list, label = "F1-Score")
    plt.legend()
    plt.title("Plotting classification accuracy, precision, recall and F1-score␣
 ↪over a different number of Ks")
    plt.xlabel("K")
    plt.ylabel("Value")
    plt.show()
```

[28]:
```
# Loading and Preprocessing Cancer Dataset
import pandas as pd
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Load CSV file
df = pd.read_csv("/content/cancer.csv")
print("CSV Shape:", df.shape)
df.head()

# Drop ID and diagnosis column, and extract labels
X = df.drop(['id', 'diagnosis'], axis=1).values
Y = df['diagnosis'].map({'M': 1, 'B': 0}).values

# Impute missing values
imputer = SimpleImputer(strategy='mean')
X = imputer.fit_transform(X)

# Split and scale
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.20,␣
 ↪random_state=42)

sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
```

```
CSV Shape: (569, 33)
```

Problem 4:

[29]:
```
# perform PCA + logistic regression
k_list, acc_list, precision_list, recall_list, f1score_list =␣
 ↪logist_model_training_pca(X, Y)
```

```
K = 1
Accuracy: 0.9122807017543859
Precision: 0.90625
Recall: 0.8055555555555556
```

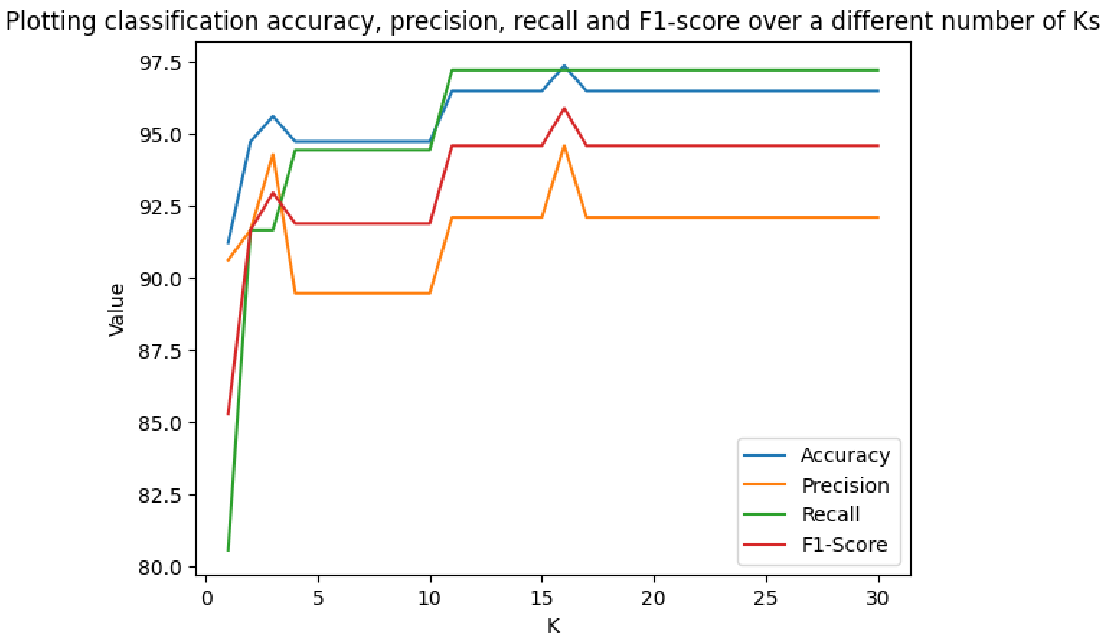
```
F1-Score: 0.8529411764705882
K = 2
Accuracy: 0.9473684210526315
Precision: 0.9166666666666666
Recall: 0.9166666666666666
F1-Score: 0.9166666666666666
K = 3
Accuracy: 0.956140350877193
Precision: 0.9428571428571428
Recall: 0.9166666666666666
F1-Score: 0.9295774647887324
K = 4
Accuracy: 0.9473684210526315
Precision: 0.8947368421052632
Recall: 0.9444444444444444
F1-Score: 0.918918918918919
K = 5
Accuracy: 0.9473684210526315
Precision: 0.8947368421052632
Recall: 0.9444444444444444
F1-Score: 0.918918918918919
K = 6
Accuracy: 0.9473684210526315
Precision: 0.8947368421052632
Recall: 0.9444444444444444
F1-Score: 0.918918918918919
K = 7
Accuracy: 0.9473684210526315
Precision: 0.8947368421052632
Recall: 0.9444444444444444
F1-Score: 0.918918918918919
K = 8
Accuracy: 0.9473684210526315
Precision: 0.8947368421052632
Recall: 0.9444444444444444
F1-Score: 0.918918918918919
K = 9
Accuracy: 0.9473684210526315
Precision: 0.8947368421052632
Recall: 0.9444444444444444
F1-Score: 0.918918918918919
K = 10
Accuracy: 0.9473684210526315
Precision: 0.8947368421052632
Recall: 0.9444444444444444
F1-Score: 0.918918918918919
K = 11
Accuracy: 0.9649122807017544
```

```
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 12
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 13
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 14
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 15
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 16
Accuracy: 0.9736842105263158
Precision: 0.9459459459459459
Recall: 0.9722222222222222
F1-Score: 0.958904109589041
K = 17
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 18
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 19
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 20
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
```

```
K = 21
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 22
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 23
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 24
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 25
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 26
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 27
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 28
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 29
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
K = 30
Accuracy: 0.9649122807017544
Precision: 0.9210526315789473
```

```
Recall: 0.9722222222222222
F1-Score: 0.9459459459459459
------------------------------
Highest Classification Accuracy Achieved: 97.36842105263158 for K number = 16
```

[30]:
```
# Plot The Graph
plot_result_with_k(k_list, acc_list, precision_list, recall_list, f1score_list)
```



Problem 5: Gaussian Naive Bayes with PCA – Performance Evaluation

[ ]:
```
# Principal Component Analysis (PCA) with Gaussian Naive Bayes (GNB)
k_list, acc_list, precision_list, recall_list, f1score_list =␣
↪GaussianNB_model_training_pca(X, Y)
```

```
K = 1
Accuracy: 0.9122807017543859
Precision: 0.90625
Recall: 0.8055555555555556
F1-Score: 0.8529411764705882
K = 2
Accuracy: 0.8947368421052632
Precision: 0.9
Recall: 0.75
F1-Score: 0.8181818181818182
K = 3
Accuracy: 0.868421052631579
Precision: 0.8387096774193549
```

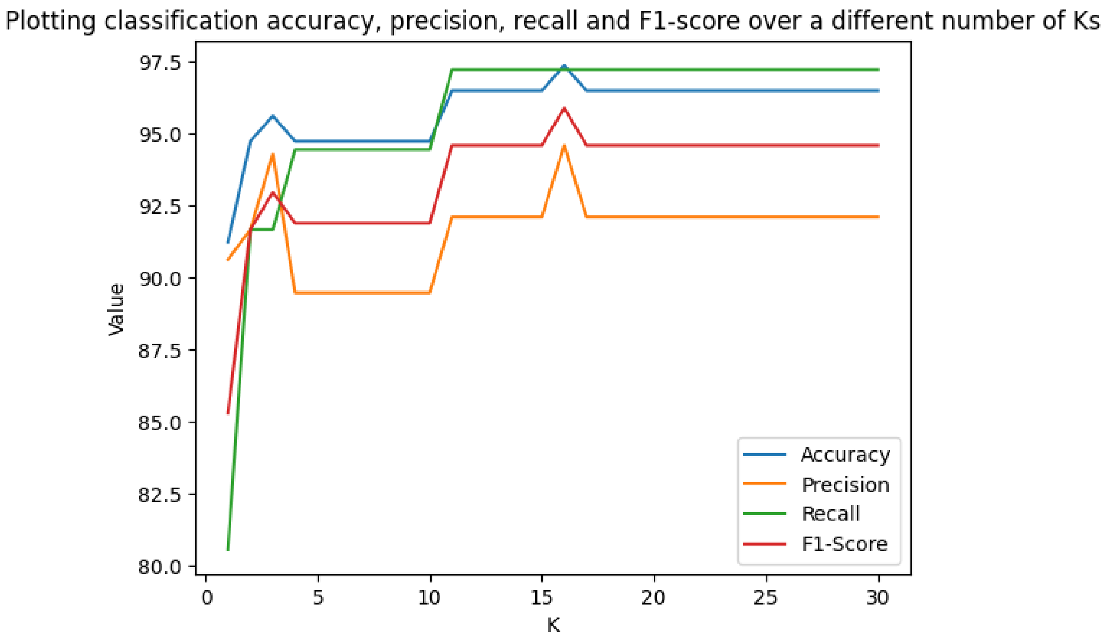
```
Recall: 0.7222222222222222
F1-Score: 0.7761194029850746
K = 4
Accuracy: 0.9035087719298246
Precision: 0.8787878787878788
Recall: 0.8055555555555556
F1-Score: 0.8405797101449275
K = 5
Accuracy: 0.9122807017543859
Precision: 0.8823529411764706
Recall: 0.8333333333333334
F1-Score: 0.8571428571428571
K = 6
Accuracy: 0.9122807017543859
Precision: 0.90625
Recall: 0.8055555555555556
F1-Score: 0.8529411764705882
K = 7
Accuracy: 0.9122807017543859
Precision: 0.90625
Recall: 0.8055555555555556
F1-Score: 0.8529411764705882
K = 8
Accuracy: 0.8947368421052632
Precision: 0.8529411764705882
Recall: 0.8055555555555556
F1-Score: 0.8285714285714286
K = 9
Accuracy: 0.9035087719298246
Precision: 0.8571428571428571
Recall: 0.8333333333333334
F1-Score: 0.8450704225352113
K = 10
Accuracy: 0.8947368421052632
Precision: 0.8333333333333334
Recall: 0.8333333333333334
F1-Score: 0.8333333333333334
K = 11
Accuracy: 0.9035087719298246
Precision: 0.8378378378378378
Recall: 0.8611111111111112
F1-Score: 0.8493150684931506
K = 12
Accuracy: 0.9035087719298246
Precision: 0.8378378378378378
Recall: 0.8611111111111112
F1-Score: 0.8493150684931506
K = 13
```

```
Accuracy: 0.9210526315789473
Precision: 0.8648648648648649
Recall: 0.8888888888888888
F1-Score: 0.8767123287671232
K = 14
Accuracy: 0.9122807017543859
Precision: 0.8611111111111112
Recall: 0.8611111111111112
F1-Score: 0.8611111111111112
K = 15
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 16
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 17
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 18
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 19
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 20
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 21
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 22
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
```

```
F1-Score: 0.8732394366197183
K = 23
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 24
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 25
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 26
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 27
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 28
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 29
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
K = 30
Accuracy: 0.9210526315789473
Precision: 0.8857142857142857
Recall: 0.8611111111111112
F1-Score: 0.8732394366197183
------------------------------
Highest Classification Accuracy Achieved: 92.10526315789474 for K number = 13
```

[31]:

```
# Plot The Graph
plot_result_with_k(k_list, acc_list, precision_list, recall_list, f1score_list)
```


Plotting classification accuracy, precision, recall and F1-score over a different number of Ks
Value
K
Accuracy
Precision
Recall
F1-Score
97.5
95.0
92.5
90.0
87.5
85.0
82.5
80.0
0
5
10
15
20
25
30