ЛАБОРАТОРНА РОБОТА № 2

ПОРІВНЯННЯ МЕТОДІВ КЛАСИФІКАЦІЇ ДАНИХ

Мета: використовуючи спеціалізовані бібліотеки та мову програмування Python дослідити різні методи класифікації даних та навчитися їх порівнювати..

Хід роботи:

Посилання Git: https://github.com/bobbyboy1710/AI/tree/main/lab2

Завдання 2.1. Класифікація за допомогою машин опорних векторів (SVM)

Числові ознаки: age, flnwgt, education-num, capital-gain, capital-loss, hours-per-week; категоріальні: workclass, education, marital-status, occupation, relationship, race, sex, native-country.

Лістинг програми:

```
import numpy as np
import matplotlib.pyplot as plt     # "plt" is not accessed
from sklearn import preprocessing, metrics     # "metrics" is not accessed
from sklearn.svm import LinearSVC
from sklearn.multiclass import OneVsOneClassifier
from sklearn.model_selection import cross_val_score,  train_test_split


input_file = 'income_data.txt'
X = []
y = []
count_class1 = 0
count_class2 = 0
max_datapoints = 30000
with open(input_file, 'r') as f:
    for line in f.readlines():
        if count_class1 >= max_datapoints and count_class2 >= max_datapoints:
            break
        if '?' in line:
            data = line[:-1].split(', ')
            if data[-1] == '<=50K' and count_class1 < max_datapoints:
                X.append(data)
                count_class1 += 1

            if data[-1] == '>50K' and count_class2 < max_datapoints:
                X.append(data)
                count_class2 += 1


X = np.array(X)
label_encoder = []
X_encoded = np.empty(X.shape)
for i, item in enumerate(X[0]):
    if item.isdigit():
        X_encoded[:, i] = X[:, i]
    else:
        label_encoder.append(preprocessing.LabelEncoder())
        X_encoded[:, i] = label_encoder[-1].fit_transform(X[:, i])

X = X_encoded[:, :-1].astype(int)
y = X_encoded[:, -1].astype(int)
classifier = OneVsOneClassifier(LinearSVC(random_state=0))
classifier.fit(X, y)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=5)
```

```
X = X_encoded[:, :-1].astype(int)
y = X_encoded[:, -1].astype(int)
classifier = OneVsOneClassifier(LinearSVC(random_state=0))
classifier.fit(X, y)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=5)
classifier = OneVsOneClassifier(LinearSVC(random_state=0))
classifier.fit(X_train, y_train)
y_test_pred = classifier.predict(X_test)
num_folds = 3


input_data = ['37', 'Private', '215646', 'HS-grad', '9', 'Never-married',
              'Handlers-cleaners', 'Not-in-family', 'White', 'Male', '0', '0', '40', 'United-States']
input_data_encoded = [-1] * len(input_data)
count = 0
for i, item in enumerate(input_data):
    if item.isdigit():
        input_data_encoded[i] = int(input_data[i])

    else:
        tmp = []
        tmp.append(input_data[i])
        input_data_encoded[i] = int(label_encoder[count].transform(tmp))
        count += 1
        tmp = []


input_data_encoded = np.array(input_data_encoded).reshape(1, -1)
predicted_class = classifier.predict(input_data_encoded)
accuracy_values = cross_val_score(classifier,
                                  X, y, scoring='accuracy', cv=num_folds)
print("Accuracy: " + str(round(100 * accuracy_values.mean(), 2)) + "%")

precision_values = cross_val_score(classifier,
                                   X, y, scoring='precision_weighted', cv=num_folds)
print("Precision: " + str(round(100 * precision_values.mean(), 2)) + "%")

recall_values = cross_val_score(classifier,
                                X, y, scoring='recall_weighted', cv=num_folds)
print("Recall: " + str(round(100 * recall_values.mean(), 2)) + "%")
f1_values = cross_val_score(classifier,
                            X, y, scoring='f1_weighted', cv=num_folds)
print("F1: " + str(round(100 * f1_values.mean(), 2)) + "%")
print('Predicted class is: ',
      label_encoder[-1].inverse_transform(predicted_class)[0])
```

Результат роботи програми:

```
AI/lab2 on  main [?]
→ python3 -W ignore LR_2_task1.py
Accuracy: 64.55%
Precision: 86.34%
Recall: 64.55%
F1: 59.63%
Predicted class is:  <=50K
```

Тестова точка належить до класу ‘<=50К’.

Завдання 2.2. Порівняння якості класифікаторів SVM з нелінійними ядрами

Результати роботи класифікаторів:

```
AI/lab2 on  main [?]
→ python3 -W ignore LR_2_task2_1.py
================Poly kernel==================================

Accuracy: 86.41%
Precision: 85.43%
Recall: 86.41%
F1: 80.52%
Predicted class is:  <=50K
------
```

```
AI/lab2 on  main [?]
→ python3 -W ignore LR_2_task2_2.py
=============Gaussian kernel================

Accuracy: 86.58%
Precision: 88.39%
Recall: 86.58%
F1: 80.77%
Predicted class is:  <=50K
```

```
AI/lab2 on  main [?]
→ python3 -W ignore LR_2_task2_3.py
====================Sigmoid kernel====================

Accuracy: 86.33%
Precision: 83.58%
Recall: 86.33%
F1: 80.19%
Predicted class is:  <=50K
```

Завдання 2.3. Порівняння якості класифікаторів на прикладі класифікації сортів ірисів

Код програми:

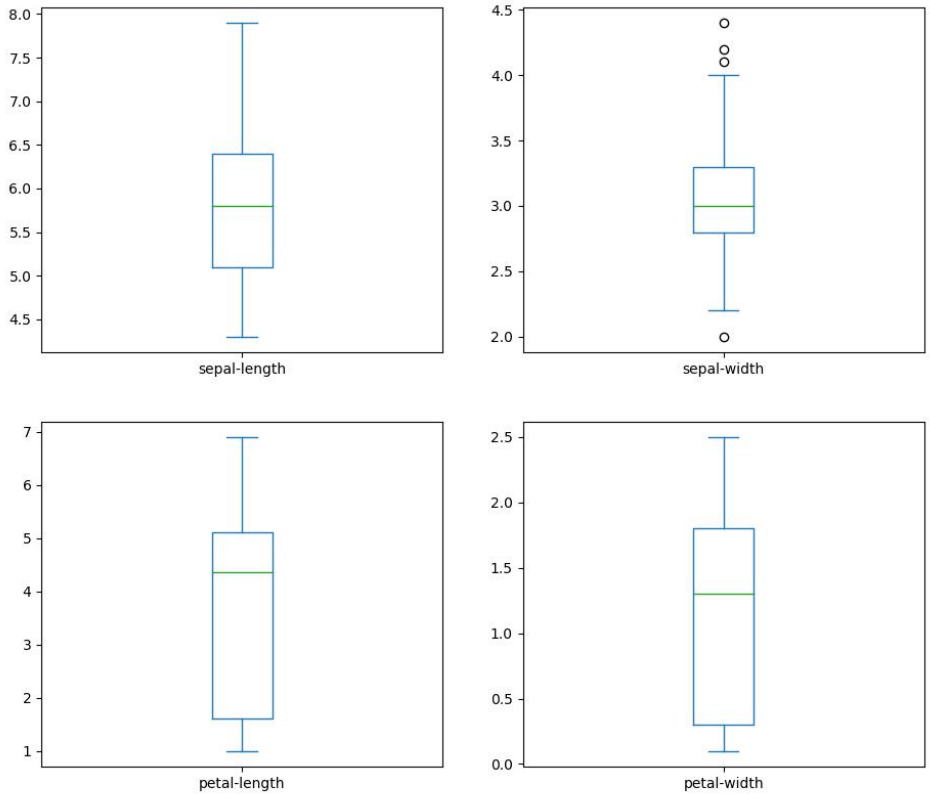
```
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/iris.csv"
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'class']
dataset = read_csv(url, names=names)

array = dataset.values

X = array[:, 0:4]
y = array[:, 4]
X_train, X_validation, Y_train, Y_validation = train_test_split(
    X, y, test_size=0.20, random_state=1)
models = []
models.append(('LR', LogisticRegression(
    solver='liblinear', multi_class='ovr')))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC(gamma='auto')))
results = []
names = []

for name, model in models:
    kfold = StratifiedKFold(n_splits=10, random_state=1, shuffle=True)
    cv_results = cross_val_score(
        model, X_train, Y_train, cv=kfold, scoring='accuracy')
    results.append(cv_results)
    names.append(name)
    print('%s: %f (%f)' % (name, cv_results.mean(), cv_results.std()))
# pyplot.boxplot(results, labels=names)
# pyplot.title('Algorithm Comparison')
# pyplot.show()

model = SVC(gamma='auto')
model.fit(X_train, Y_train)
predictions = model.predict(X_validation)
# print(accuracy_score(Y_validation, predictions))
# print(confusion_matrix(Y_validation, predictions))
# print(classification_report(Y_validation, predictions))


X_new = np.array([[5, 2.9]])     ■ Argument of type "list[list[int | float]]" cannot be assigned to para
knn = KNeighborsClassifier(n_neighbors=5)
x_train, x_test, y_train, y_test = train_test_split(iris_dataset.data[:, 2:4],     ■ Cannot access membe
                                                    iris_dataset['target'],     ■ Argument of type "Lite
                                                    random_state=0)
knn_model = knn.fit(x_train, y_train)
prediction = knn.predict(X_new)
predictions = knn.predict(x_test)
accuracy = accuracy_score(y_test, predictions)
print(f'Accuracy: {accuracy}')
print("forecast: {}".format(iris_dataset['target_names'][prediction[0]]))     ■ Argument of type "Litera
```

Результат виконання програми:

```
→ python3 -W ignore LR_2_task3.py
iris_dataset's keys: dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_na
mes', 'filename', 'data_module'])
.. _iris_dataset:

Iris plants dataset
--------------------

**Data Set Characteristics:**

    :Number of Instances: 150 (50 in each of three classes)
    :Number of Attributes: 4 numeric, predictive attributes and the class
    :Attribute Information:
        - sepal length in cm
        - sepal width in cm
        - petal length in cm
        - petal width in cm
        - class:
                - Iris-Setosa
                - Iris-Versicolour
                - Iris-Virginica

    :Summary Statistics:

    ============== ==== ==== ======= ===== ====================
                    Min  Max   Mean    SD   Class Correlation
    ============== ==== ==== ======= ===== ====================
    sepal length:   4.3  7.9   5.84   0.83    0.7826
    sepal width:    2.0  4.4   3.05   0.43   -0.4194
    petal length:   1.0  6.9   3.76   1.76    0.9490  (high!)
    petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)
    ============== ==== ==== ======= ===== ====================

    :Missing Attribute Values: None
    :Class Distribution: 33.3% for each of 3 classes.
    :Creator: R.A. Fisher
    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
    :Date: July, 1988

The famous Iris database, first used by Sir R.A. Fisher. The dataset is taken
from Fisher's paper. Note that it's the same as in R, but not as in the UCI
Machine Learning Repository, which has two wrong data points.

This is perhaps the best known database to be found in the
pattern recognition literature.  Fisher's paper is a classic in the field and
is referenced frequently to this day.  (See Duda & Hart, for example.)  The
data set contains 3 classes of 50 instances each, where each class refers to a
type of iris plant.  One class is linearly separable from the other 2; the
latter are NOT linearly separable from each other.

.. topic:: References

   - Fisher, R.A. "The use of multiple measurements in taxonomic problems"
     Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to
```

```
   - Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analysis.
     (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.
   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System
     Structure and Classification Rule for Recognition in Partially Exposed
     Environments".  IEEE Transactions on Pattern Analysis and Machine
     Intelligence, Vol. PAMI-2, No. 1, 67-71.
   - Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEEE Transactions
     on Information Theory, May 1972, 431-433.
   - See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II
     conceptual clustering system finds 3 classes in the data.
   - Many, many more ...
...
target names: ['setosa' 'versicolor' 'virginica']
feature names: ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)
']
type of data array: <class 'numpy.ndarray'>
shape of data array: (5, 4)
type of target array: <class 'numpy.ndarray'>
targets: [0 0 0 0 0]
Accuracy: 0.9736842105263158
forecast: virginica
```

Побудовані графіки:



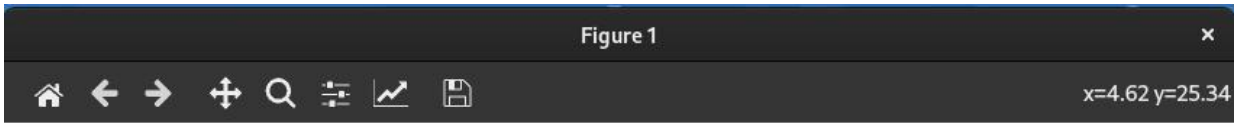
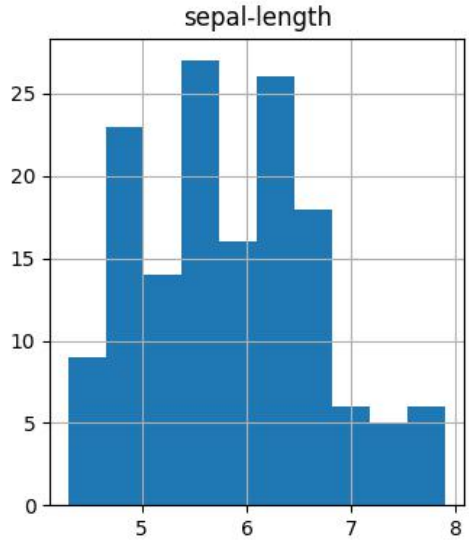
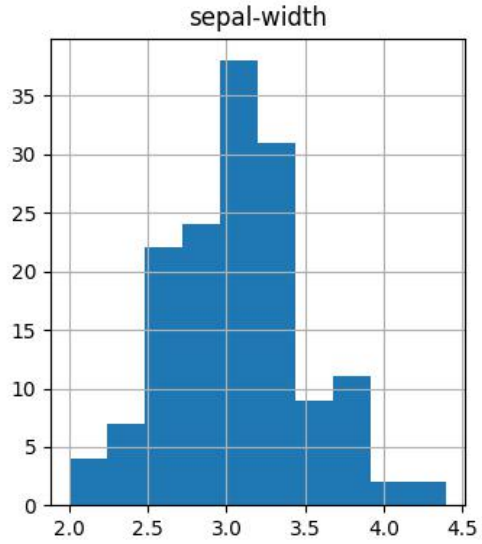
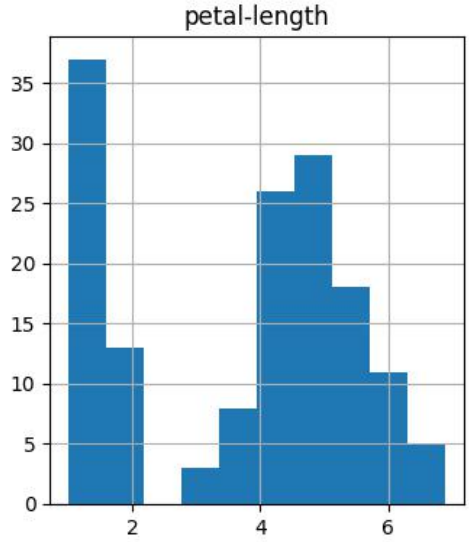
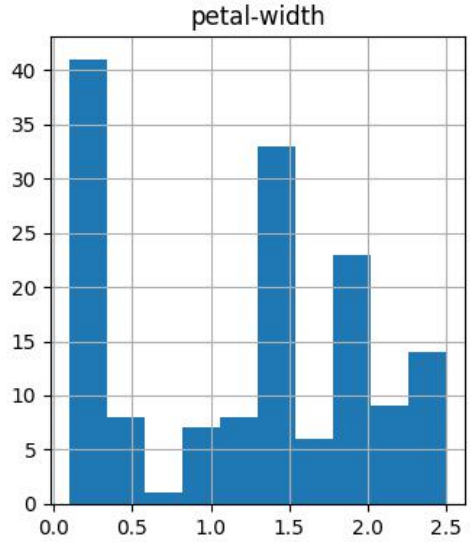


Figure 1
x=4.62 y=25.34


sepal-length
0
5
10
15
20
25
5
6
7
8


sepal-width
0
5
10
15
20
25
30
35
2.0
2.5
3.0
3.5
4.0
4.5


petal-length
0
5
10
15
20
25
30
35
2
4
6


petal-width
0
5
10
15
20
25
30
35
40
0.0
0.5
1.0
1.5
2.0
2.5

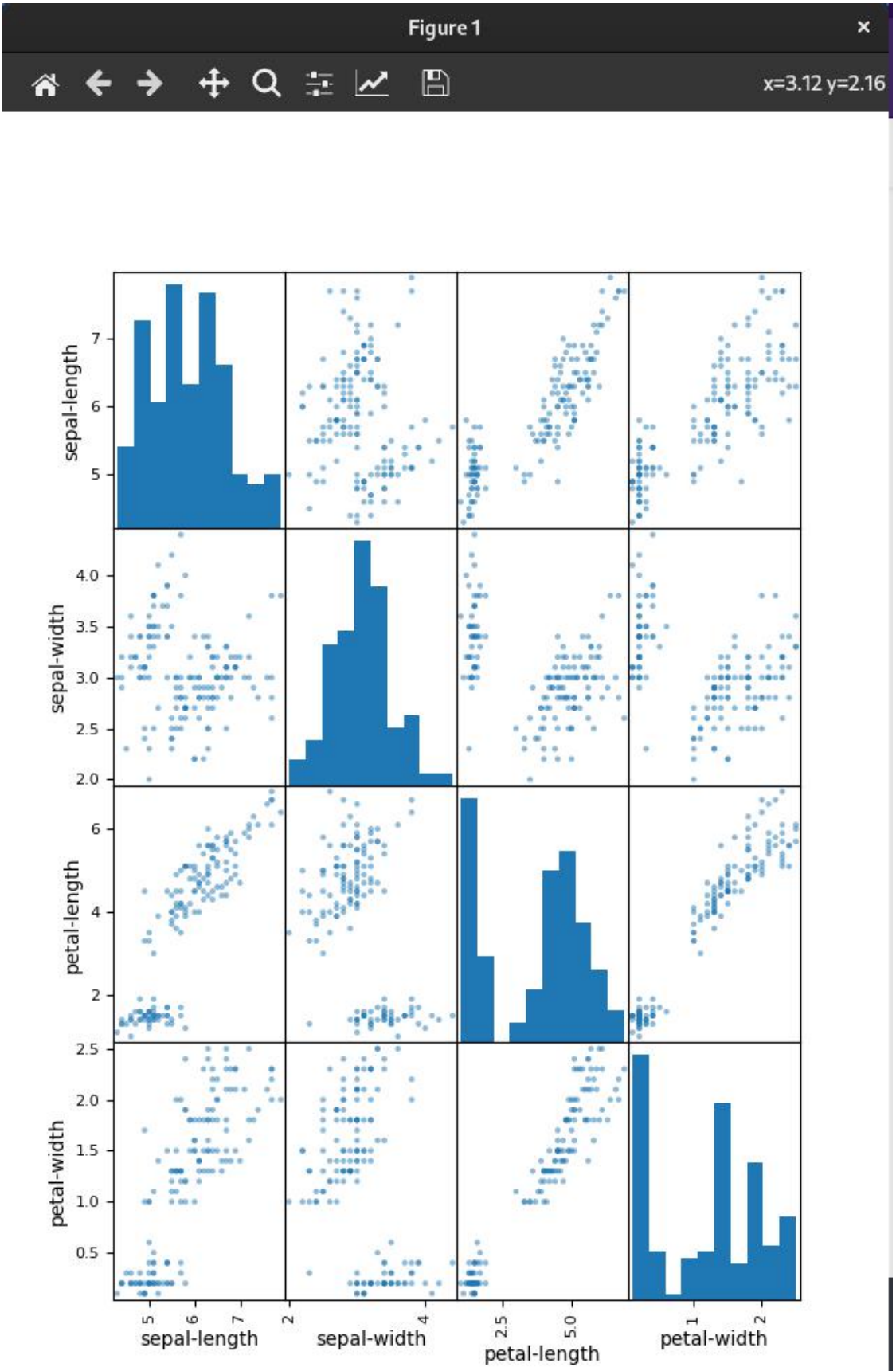


Figure 1
x=3.12 y=2.16
sepal-length
sepal-width
petal-length
petal-width

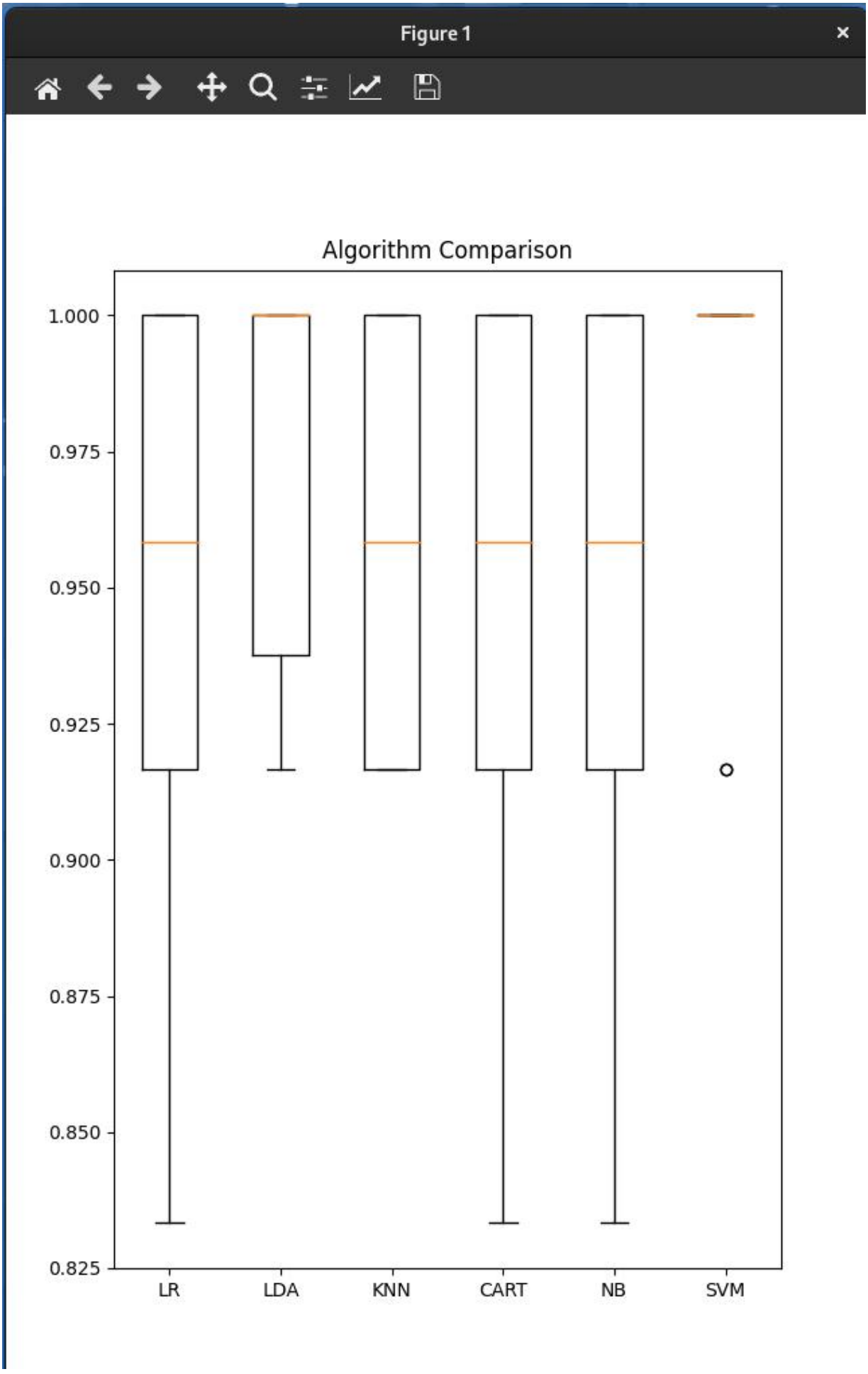


Figure 1
Algorithm Comparison
1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.825
LR
LDA
KNN
CART
NB
SVM

Результат роботи програми:

```
targets: [0 0 0 0 0]
LR: 0.941667 (0.065085)
LDA: 0.975000 (0.038188)
KNN: 0.958333 (0.041667)
CART: 0.950000 (0.055277)
NB: 0.950000 (0.055277)
SVM: 0.983333 (0.033333)
0.9666666666666667
[[11  0  0]
 [ 0 12  1]
 [ 0  0  6]]
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        11
Iris-versicolor       1.00      0.92      0.96        13
 Iris-virginica       0.86      1.00      0.92         6

       accuracy                           0.97        30
      macro avg       0.95      0.97      0.96        30
   weighted avg       0.97      0.97      0.97        30

Accuracy: 0.9736842105263158
forecast: virginica
```

За результатами тренування вдалося досягти точності 0.97 та встановити, що квітка належить до класу virginica.

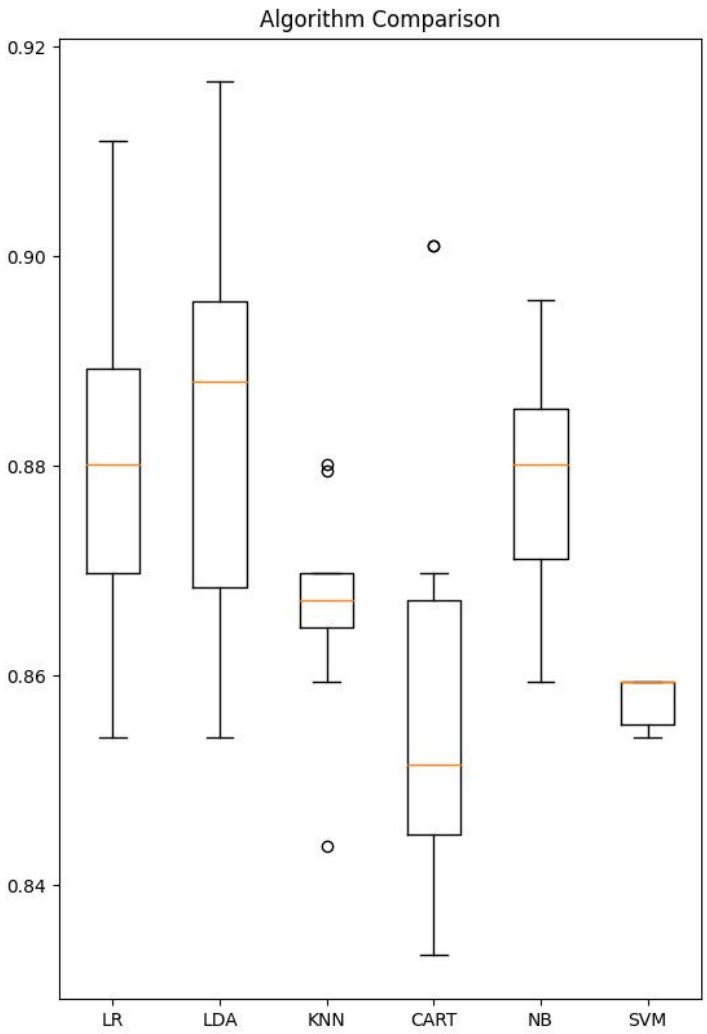
Завдання 2.4. Порівняння якості класифікаторів для набору даних завдання 2.1

Код програми:

```
from matplotlib import pyplot
from sklearn import preprocessing
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import StratifiedKFold, cross_val_score, train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
import numpy as np


input_file = 'income_data.txt'
X = []
y = []
count_class1 = 0
count_class2 = 0
max_datapoints = 30000
with open(input_file, 'r') as f:
    for line in f.readlines():
        if count_class1 >= max_datapoints and count_class2 >= max_datapoints:
            break
        if '?' in line:
            data = line[:-1].split(', ')
            if data[-1] == '<=50K' and count_class1 < max_datapoints:
                X.append(data)
                count_class1 += 1

            if data[-1] == '>50K' and count_class2 < max_datapoints:
                X.append(data)
                count_class2 += 1


X = np.array(X)
label_encoder = []
X_encoded = np.empty(X.shape)
for i, item in enumerate(X[0]):
    if item.isdigit():
        X_encoded[:, i] = X[:, i]
    else:
        label_encoder.append(preprocessing.LabelEncoder())
        X_encoded[:, i] = label_encoder[-1].fit_transform(X[:, i])

X = X_encoded[:, :-1].astype(int)
y = X_encoded[:, -1].astype(int)


X_train, X_validation, Y_train, Y_validation = train_test_split(
    X, y, test_size=0.20, random_state=1)
models = []
models.append(('LR', LogisticRegression(
    solver='liblinear', multi_class='ovr')))
models.append(('LDA', LinearDiscriminantAnalysis()))
```

```
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC(gamma='auto')))
results = []
names = []
for name, model in models:
    kfold = StratifiedKFold(n_splits=10, random_state=1, shuffle=True)
    cv_results = cross_val_score(
        model, X_train, Y_train, cv=kfold, scoring='accuracy')
    results.append(cv_results)
    names.append(name)
    print('%s: %f (%f)' % (name, cv_results.mean(), cv_results.std()))
pyplot.boxplot(results, labels=names)
pyplot.title('Algorithm Comparison')
pyplot.show()
```

Результати роботи програми:




```
AI/lab2 on ᚠ main [?] took 1m 28s 665ms
➜ python3 -W ignore LR_2_task4.py
LR: 0.880683 (0.016293)
LDA: 0.885883 (0.019384)
KNN: 0.866604 (0.009853)
CART: 0.860338 (0.022359)
NB: 0.879633 (0.010957)
SVM: 0.857739 (0.002348)
```

Порівнявши алгоритми за показником точності можна дійти висновку, що найкращим є алгоритм NB.

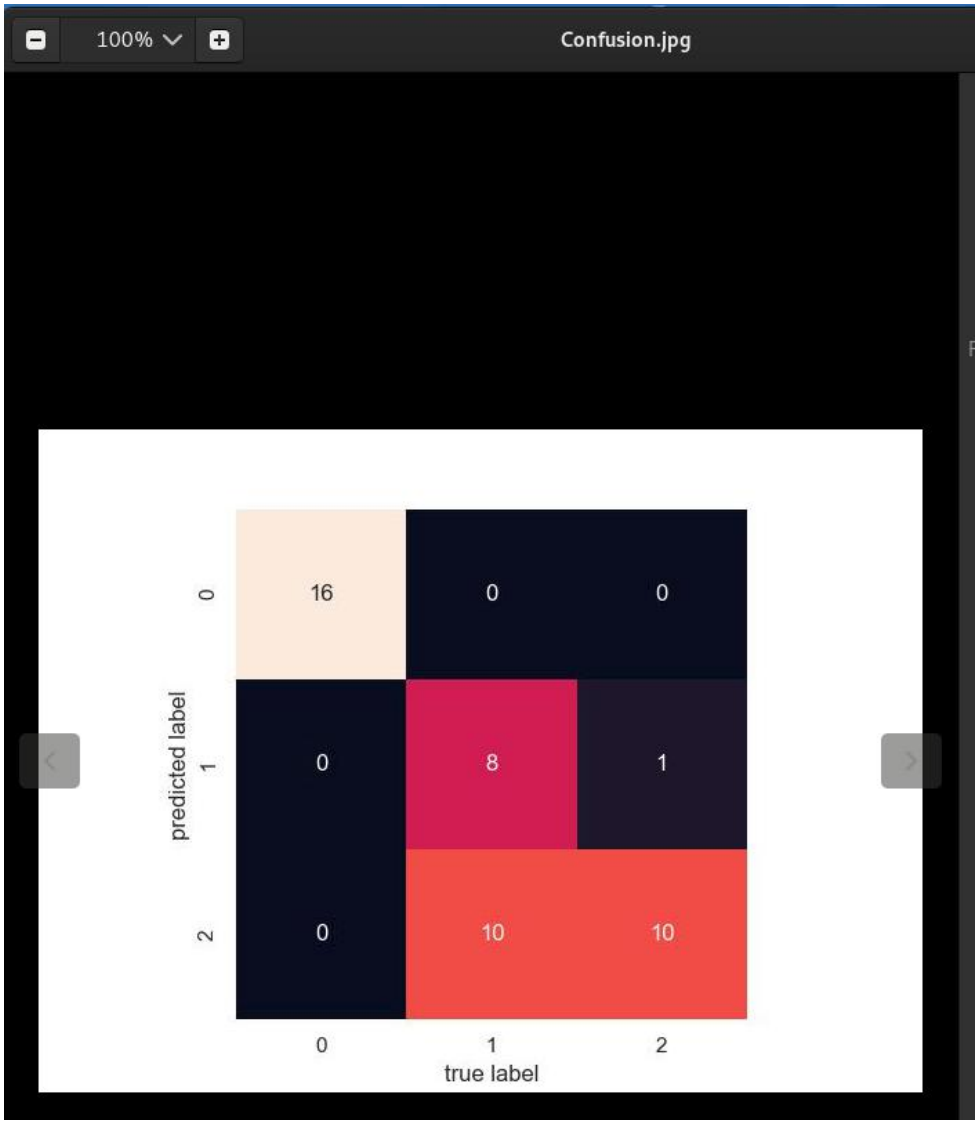
Завдання 2.5. Класифікація даних лінійним класифікатором Ridge

Код програми:

```
lab2› LR_2_task5.py
import seaborn as sns
from io import BytesIO  # needed for plot
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
from sklearn import metrics
import numpy as np
from sklearn.datasets import load_iris
from sklearn.linear_model import RidgeClassifier
from sklearn.model_selection import train_test_split
iris = load_iris()
X, y = iris.data, iris.target
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=0)
clf = RidgeClassifier(tol=1e-2, solver="sag")
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
print('Accuracy:', np.round(metrics.accuracy_score(y_test, y_pred), 4))
print('Precision:', np.round(metrics.precision_score(
    y_test, y_pred, average='weighted'), 4))
print('Recall:', np.round(metrics.recall_score(
    y_test, y_pred, average='weighted'), 4))
print('F1 Score:', np.round(metrics.f1_score(
    y_test, y_pred, average='weighted'), 4))
print('Cohen Kappa Score:', np.round(
    metrics.cohen_kappa_score(y_test, y_pred), 4))
print('Matthews Corrcoef:', np.round(
    metrics.matthews_corrcoef(y_test, y_pred), 4))
print('\t\tClassification Report:\n',
      metrics.classification_report(y_pred, y_test))
sns.set()
mat = confusion_matrix(y_test, y_pred)
sns.heatmap(mat.T, square=True, annot=True, fmt='d', cbar=False)
plt.xlabel('true label')
plt.ylabel('predicted label')
plt.savefig("Confusion.jpg")
f = BytesIO()
plt.savefig(f, format="svg")
```

Результат роботи програми:

```
→ python3 -W ignore LR_2_task5.py
Accuracy: 0.7556
Precision: 0.8333
Recall: 0.7556
F1 Score: 0.7503
Cohen Kappa Score: 0.6431
Matthews Corrcoef: 0.6831
                Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        16
           1       0.44      0.89      0.59         9
           2       0.91      0.50      0.65        20

    accuracy                           0.76        45
   macro avg       0.78      0.80      0.75        45
weighted avg       0.85      0.76      0.76        45
```



При налаштуванні класифікатора було використано такі параметри: tol (точність рішення) та solver (рішення для обрахунків). Коефіцієнт Коена Каппа є мірою узгодженості між двома спостерігачами, які оцінюють якісну змінну.

Коефіцієнт кореляції Метьюза використовується для оцінки зв'язку між результатами діагностики та станом пацієнта. Він розраховується як відношення кількості правильних діагнозів до загальної кількості діагнозів, враховуючи відсутність зв'язку випадкових результатів.

Висновки: у ході виконання даної лабораторної роботи я, використовуючи спеціалізовані бібліотеки та мову програмування Python, дослідив класифікацію даних різними методами та за допомогою метрик якості класифікації оцінив їх ефективності.