Exercise 3: Logistic Regression

CPSC 381/581: Machine Learning

Yale University

Instructor: Alex Wong

Student: Hailey Robertson

Prerequisites:

1. Enable Google Colaboratory as an app on your Google Drive account
2. Create a new Google Colab notebook, this will also create a "Colab Notebooks" directory under "MyDrive" i.e.

   ```
   /content/drive/MyDrive/Colab Notebooks
   ```

3. Create the following directory structure in your Google Drive

   ```
   /content/drive/MyDrive/Colab Notebooks/CPSC 381-581: Machine
   Learning/Exercises
   ```

4. Move the 02_exercise_linear_regression.ipynb into

   ```
   /content/drive/MyDrive/Colab Notebooks/CPSC 381-581: Machine
   Learning/Exercises
   ```

so that its absolute path is

```
/content/drive/MyDrive/Colab Notebooks/CPSC 381-581: Machine
Learning/Exercises/03_exercise_logistic_regression.ipynb
```

In this exercise, we will optimize a logistic regression model and visualize its confusion matrix. We will test them on several datasets.

Submission:

1. Implement all TODOs in the code blocks below.
2. Report your training and validation scores. Note: for full points, your training and validation scores should be above 0.8.

   ```
   ***** Experiments on the Iris dataset *****
   Training set mean accuracy: 1.0000
   Validation set mean accuracy: 0.9667
   ```

```
***** Experiments on the Breast cancer dataset *****
Training set mean accuracy: 0.9560
Validation set mean accuracy: 0.9035

***** Experiments on the Digits dataset *****
Training set mean accuracy: 1.0000
Validation set mean accuracy: 0.9694

***** Experiments on the Wine dataset *****
Training set mean accuracy: 0.9718
Validation set mean accuracy: 0.9444
```

3. List any collaborators.

   None.

Import packages

In [2]:
```
import numpy as np
import sklearn.datasets as skdata
import sklearn.metrics as skmetrics
import sklearn.preprocessing as skpreprocessing
from sklearn.linear_model import LogisticRegression
import time, warnings
import matplotlib.pyplot as plt

warnings.filterwarnings(action='ignore')
np.random.seed = 1
```

Loading data

In [3]:
```
# Load datasets
datasets = [
    skdata.load_iris(),
    skdata.load_breast_cancer(),
    skdata.load_digits(),
    skdata.load_wine()
]

dataset_names = [
    'Iris',
    'Breast cancer',
    'Digits',
    'Wine'
]
```

Training and validation loop

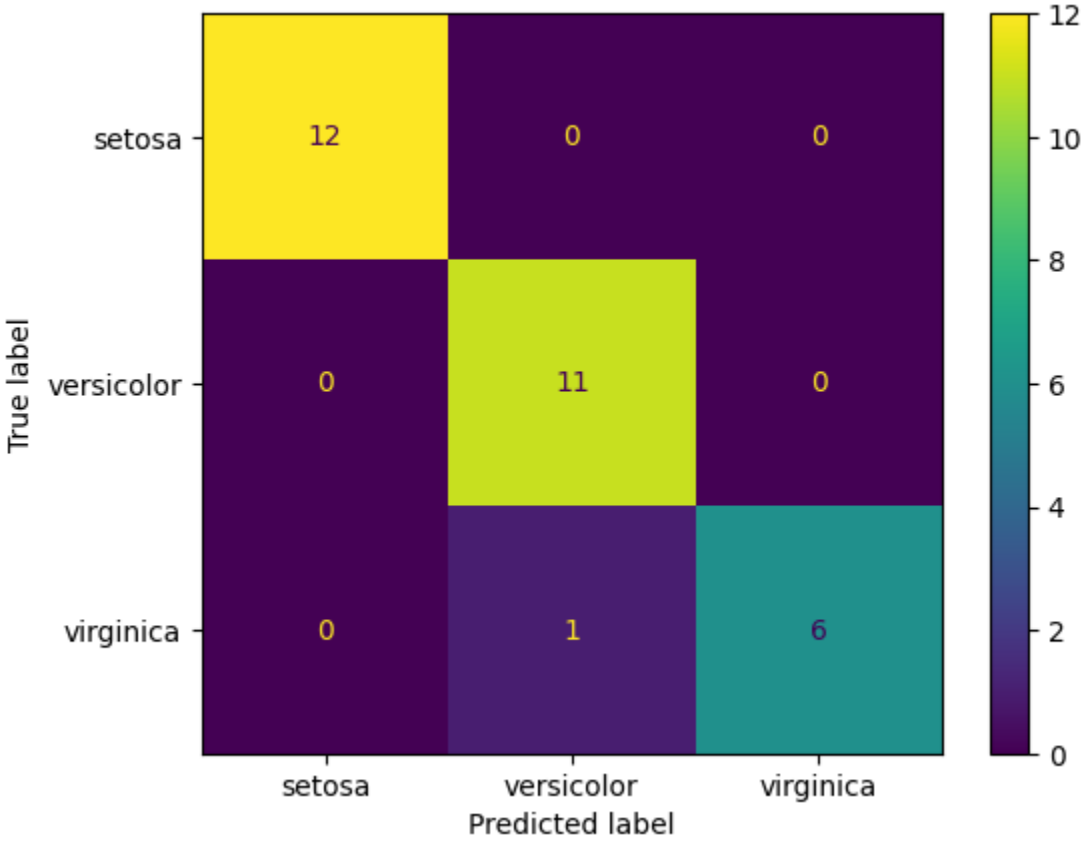
In [8]:
```
# Zip up all dataset options
dataset_options = zip(
    datasets,
```

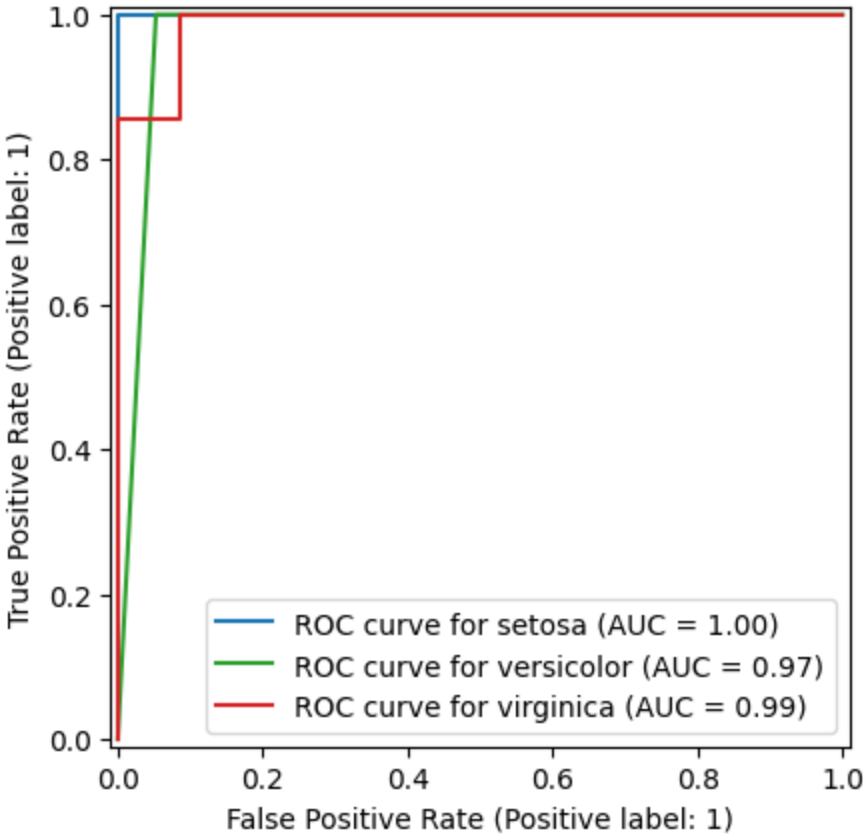
```
    dataset_names)

# Create a list of colors for display
colors = [
    'tab:blue',
    'tab:green',
    'tab:red',
    'tab:orange',
    'tab:purple',
    'tab:brown',
    'tab:pink',
    'tab:gray',
    'tab:olive'
]

for dataset, dataset_name in dataset_options:

    '''
    Create the training and validation splits
    '''
    X = dataset.data
    y = dataset.target
    labels = dataset.target_names

    # DONE: Get unique labels/targets
    y_unique = np.unique(y)

    print('Preprocessing the {} dataset ({} samples, {} feature dimensions)'

    # Shuffle the dataset based on sample indices
    shuffled_indices = np.random.permutation(X.shape[0])

    # Choose the first 80% as training set and the next 20% as validation
    train_split_idx = int(0.80 * X.shape[0])

    train_indices = shuffled_indices[0:train_split_idx]
    val_indices = shuffled_indices[train_split_idx:]

    # Select the examples from X and y to construct our training, validation
    X_train, y_train = X[train_indices, :], y[train_indices]
    X_val, y_val = X[val_indices, :], y[val_indices]

    print('***** Experiments on the {} dataset *****'.format(dataset_name))

    '''
    Train and validate logistic regression on each dataset
    '''
    # DONE: Instantiate logistic regression model with penalty=None
    model_scikit = LogisticRegression(penalty=None)

    # DONE: Train scikit-learn model
    model_scikit.fit(X_train, y_train)

    # DONE: Score model using mean accuracy on training set
    predictions_train = model_scikit.predict(X_train)
    score_train = skmetrics.accuracy_score(y_train, predictions_train)
```

```
    print('Training set mean accuracy: {:.4f}'.format(score_train))

    # DONE: Score model using mean accuracy validation set
    predictions_val = model_scikit.predict(X_val)
    score_val = skmetrics.accuracy_score(y_val, predictions_val)
    print('Validation set mean accuracy: {:.4f}'.format(score_val))

    '''
    Plot confusion matrix and receiver operating characteristic (ROC) curve
    '''

    # DONE: Create a confusion matrix using skmetrics.confusion_matrix
    confusion_matrix = skmetrics.confusion_matrix(y_val, predictions_val)

    # DONE: Create a visualization of the confusion matrix using skmetrics.C
    confusion_matrix_plot = skmetrics.ConfusionMatrixDisplay(
        confusion_matrix=confusion_matrix,
        display_labels=labels
    )

    # DONE: Display the confusion matrix using the plot function
    confusion_matrix_plot.plot()

    # DONE: Predict probabilities using LogisticRegression's predict_proba f
    probabilities_val = model_scikit.predict_proba(X_val)

    # DONE: Create a 1 x 1 subplot in a figure
    # width, height, accessed element
    fig = plt.figure()
    ax = fig.add_subplot(1, 1, 1)

    # DONE: Using scikit's preprocessing.label_binarize to convert your labe
    # Note: for binary classification label_binarize will give you a Nx1 vec
    one_hot_val = skpreprocessing.label_binarize(y_val, classes = y_unique)

    # DONE: Handle binary classification by concatenating the negative (0) c
    if len(labels) < 3:
        one_hot_val = np.concatenate([1 - one_hot_val, one_hot_val], axis =


    # DONE: For each class_id and color, create a RocCurveDisplay
    for class_id, color, label in zip(range(len(labels)), colors, labels):
        skmetrics.RocCurveDisplay.from_predictions(
            one_hot_val[:, class_id],
            probabilities_val[:, class_id],
            name="ROC curve for {}".format(label),
            color=color,
            ax=ax
        )


    # DONE: Use show() function from matplotlib (plt) to display plots
    plt.show()


    # Pause to allow plots to show
```

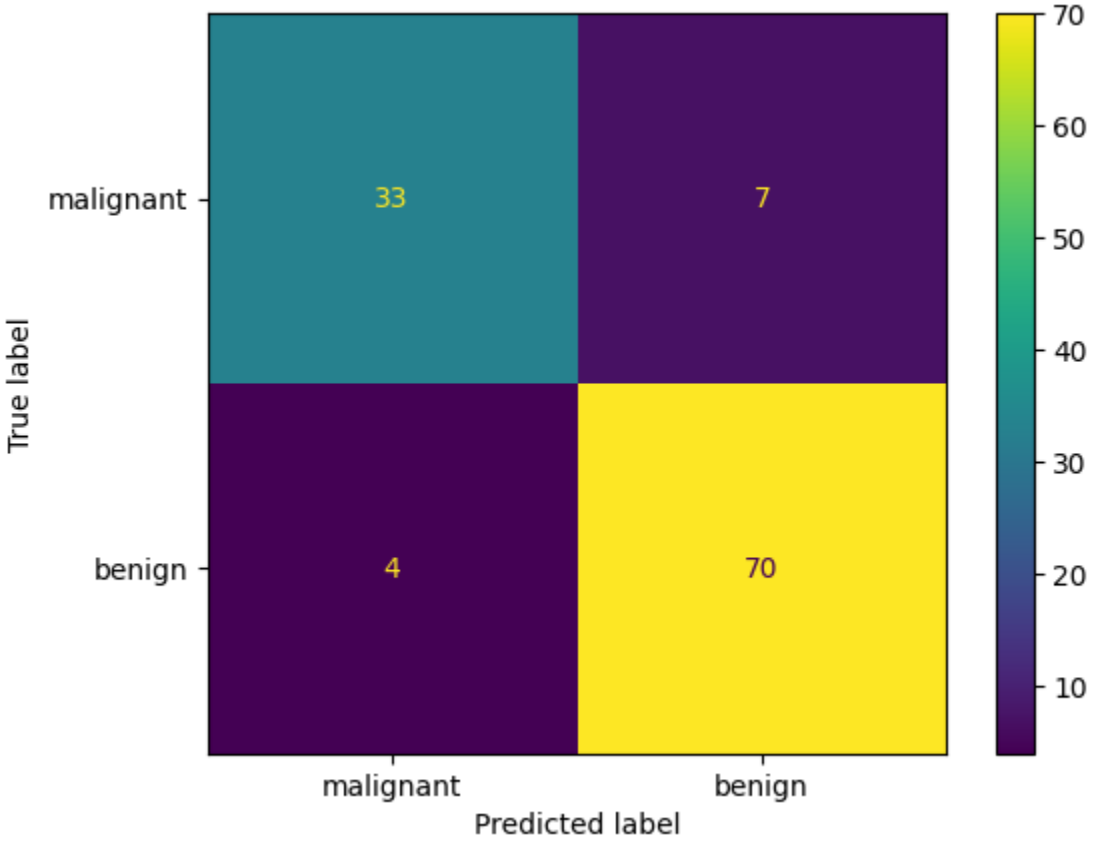
```
    time.sleep(1)
```

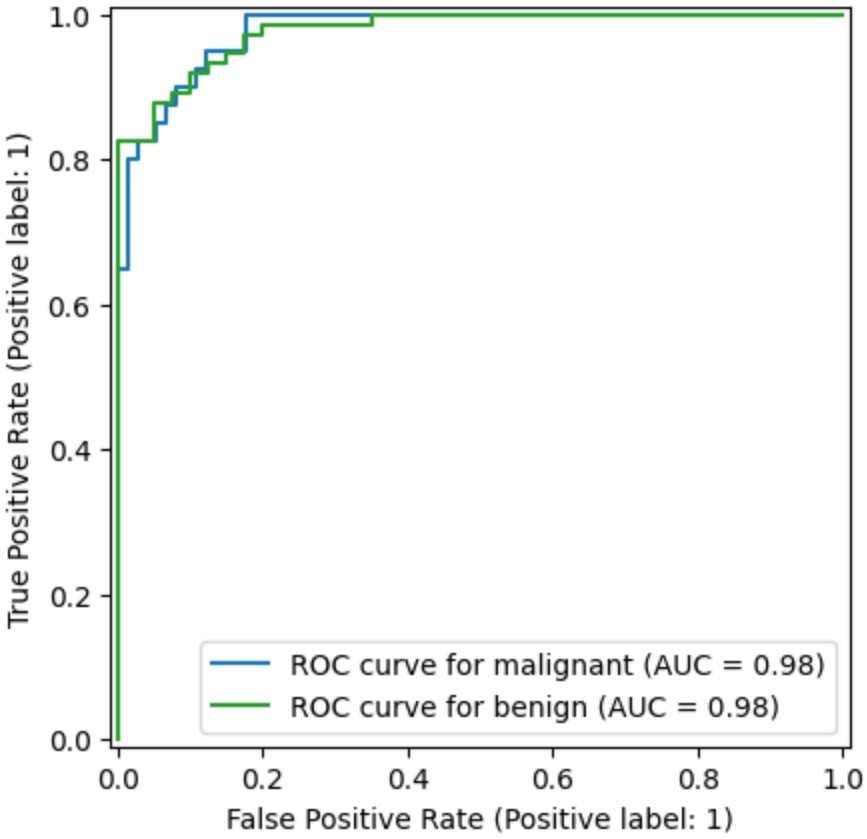
```
Preprocessing the Iris dataset (150 samples, 4 feature dimensions)
***** Experiments on the Iris dataset *****
Training set mean accuracy: 1.0000
Validation set mean accuracy: 0.9667
```



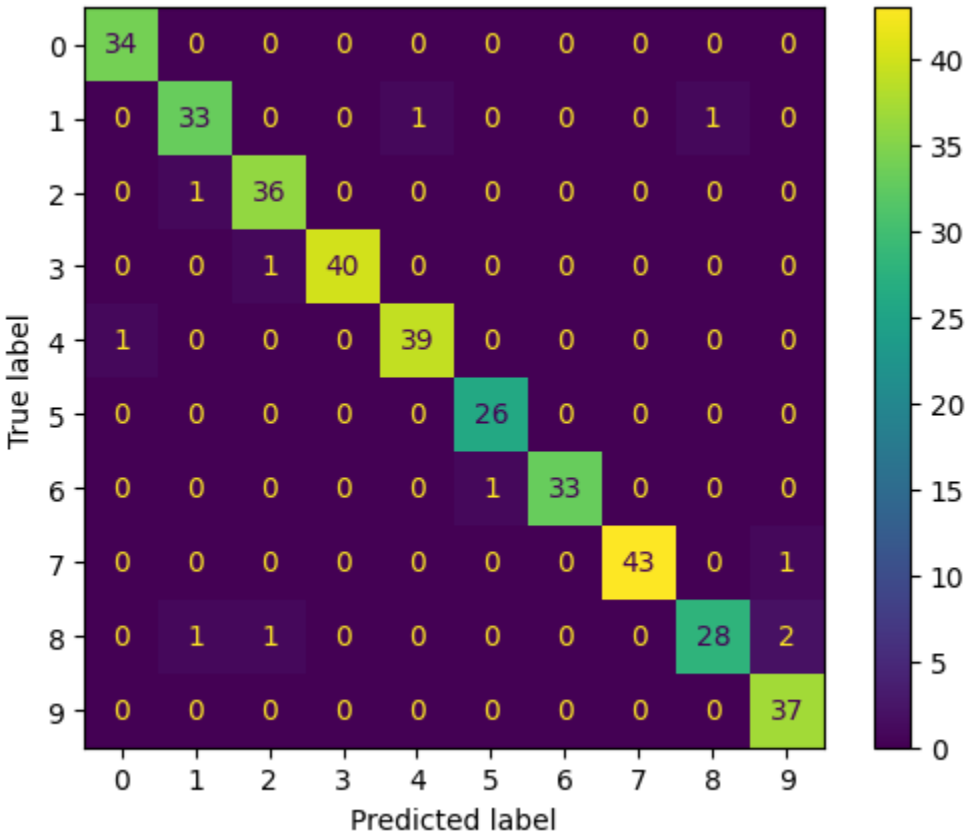


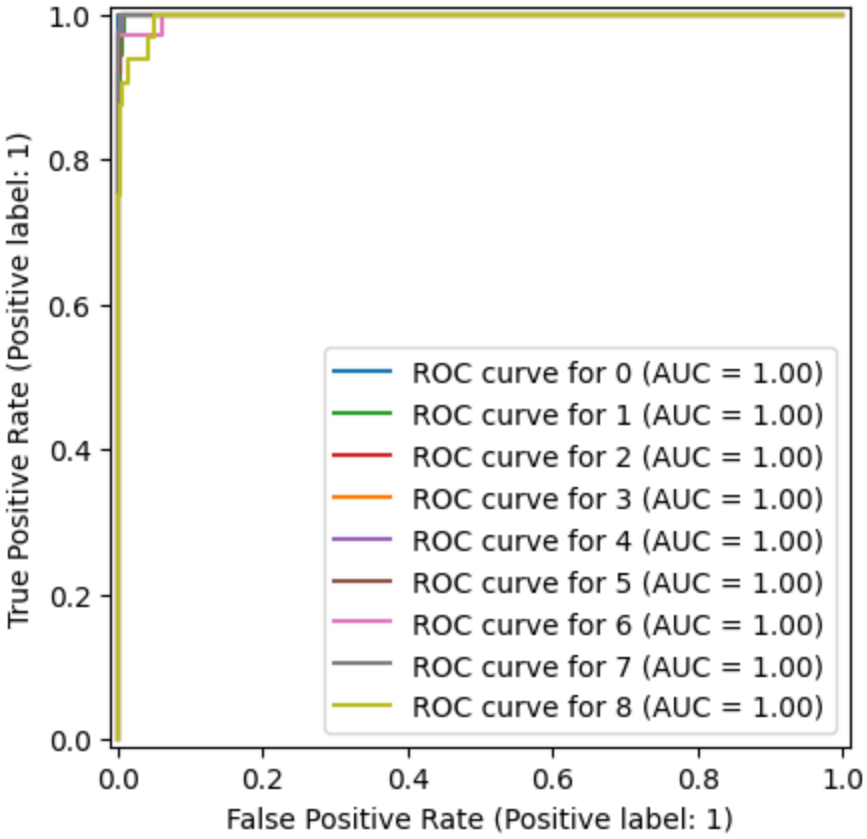

```
Preprocessing the Breast cancer dataset (569 samples, 30 feature dimensions)
***** Experiments on the Breast cancer dataset *****
Training set mean accuracy: 0.9560
Validation set mean accuracy: 0.9035
```



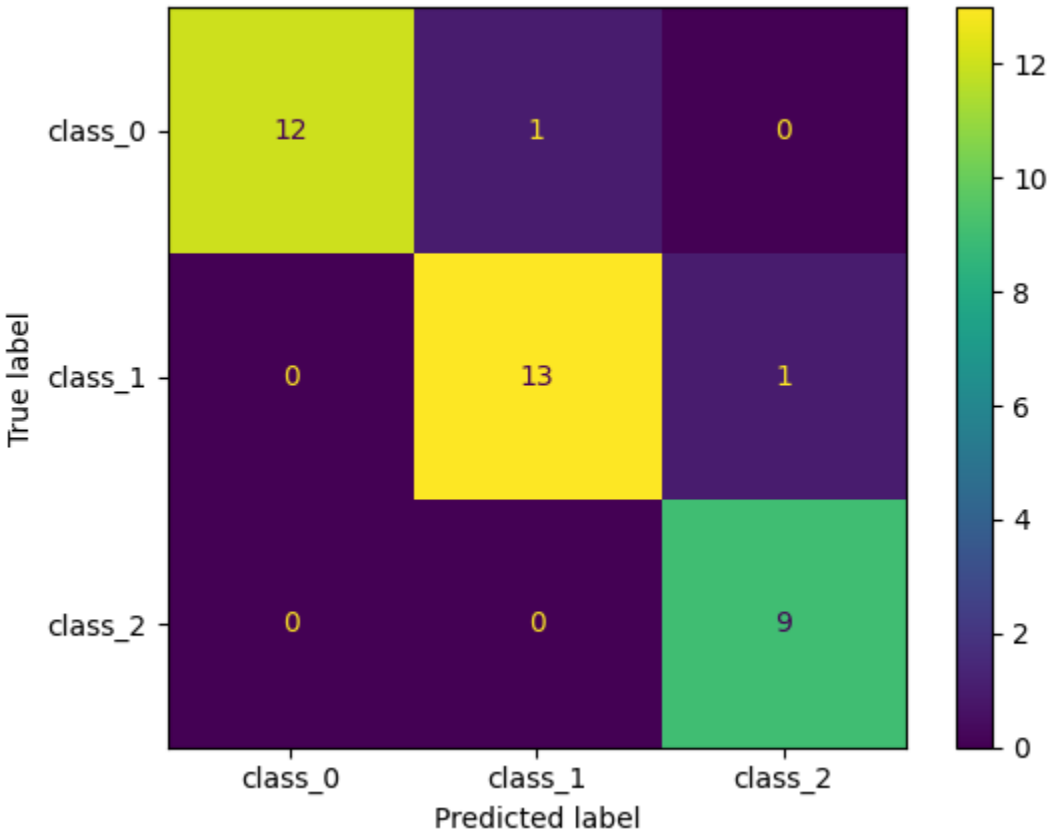


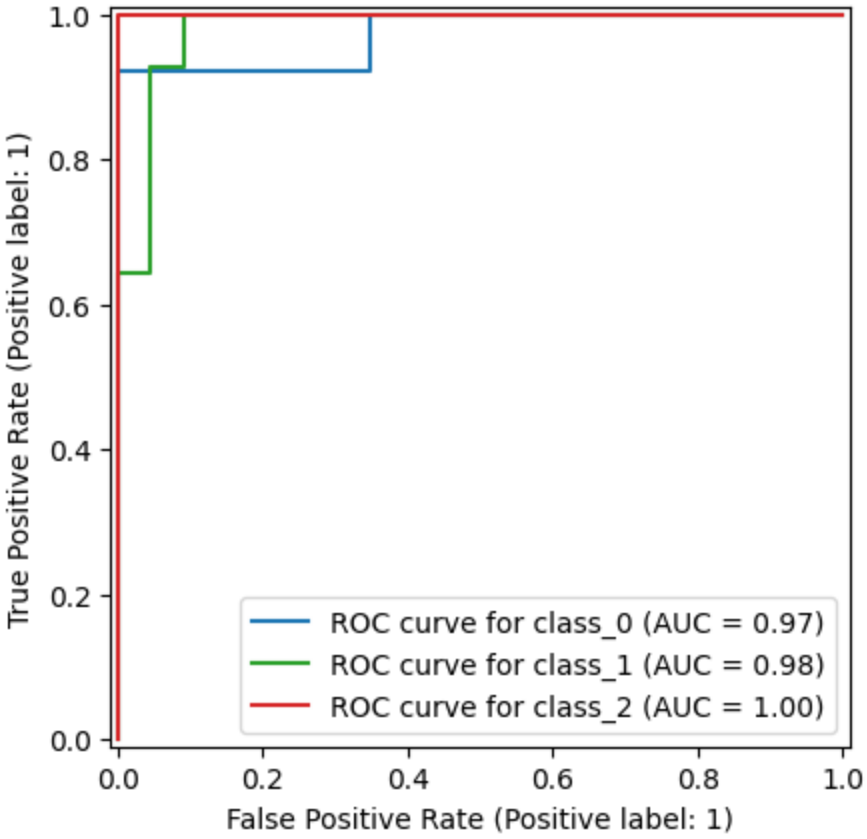

```
Preprocessing the Digits dataset (1797 samples, 64 feature dimensions)
***** Experiments on the Digits dataset *****
Training set mean accuracy: 1.0000
Validation set mean accuracy: 0.9694
```






```
Preprocessing the Wine dataset (178 samples, 13 feature dimensions)
***** Experiments on the Wine dataset *****
Training set mean accuracy: 0.9718
Validation set mean accuracy: 0.9444
```




1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate (Positive label: 1)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (Positive label: 1)
ROC curve for class_0 (AUC = 0.97)
ROC curve for class_1 (AUC = 0.98)
ROC curve for class_2 (AUC = 1.00)

In [ ]: