ML LAB ASSIGNMENT 4

22MCA1055

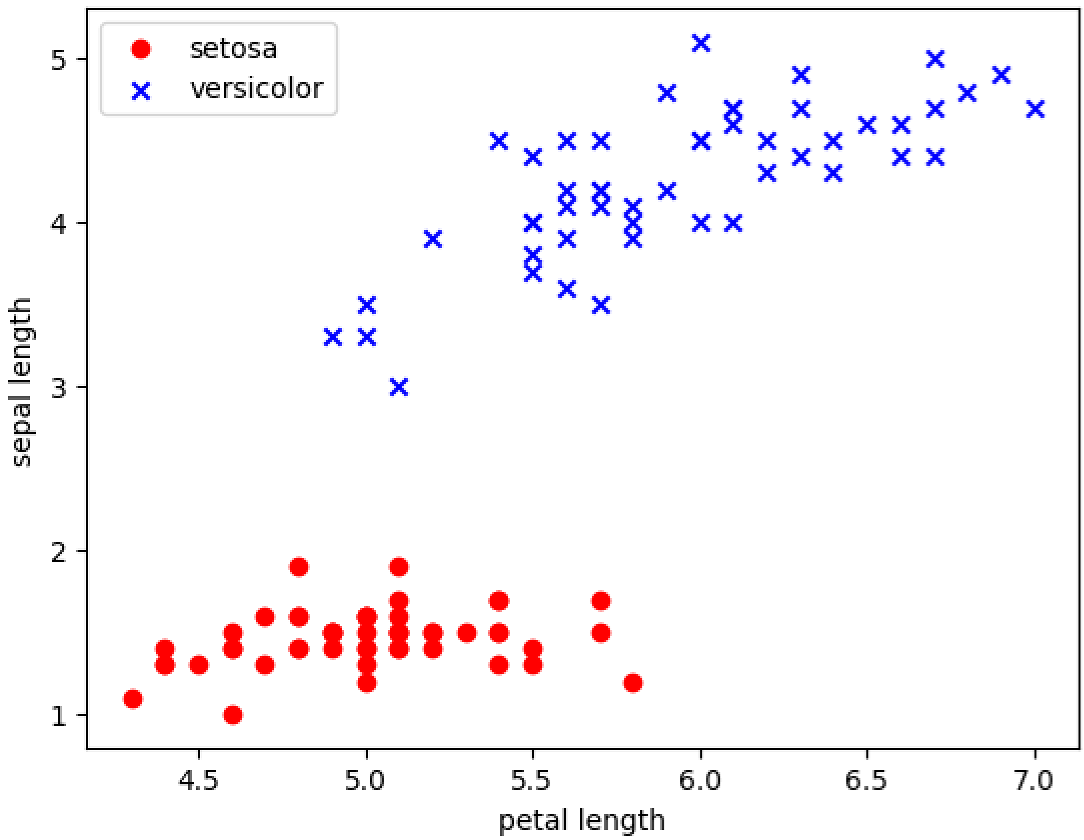
Upload a consolidated Lab Assignment File as a PDF file. Use a dataset from UCI Machine Learning Repository.

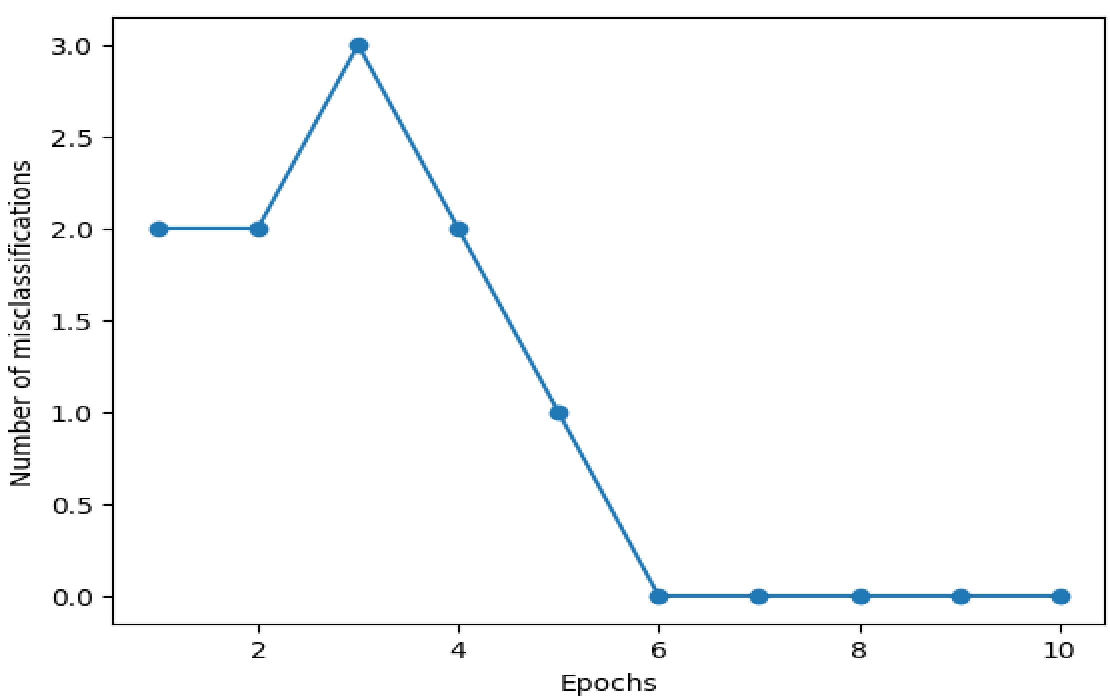
(i) Perceptron
(ii) Back Propagation Algorithm

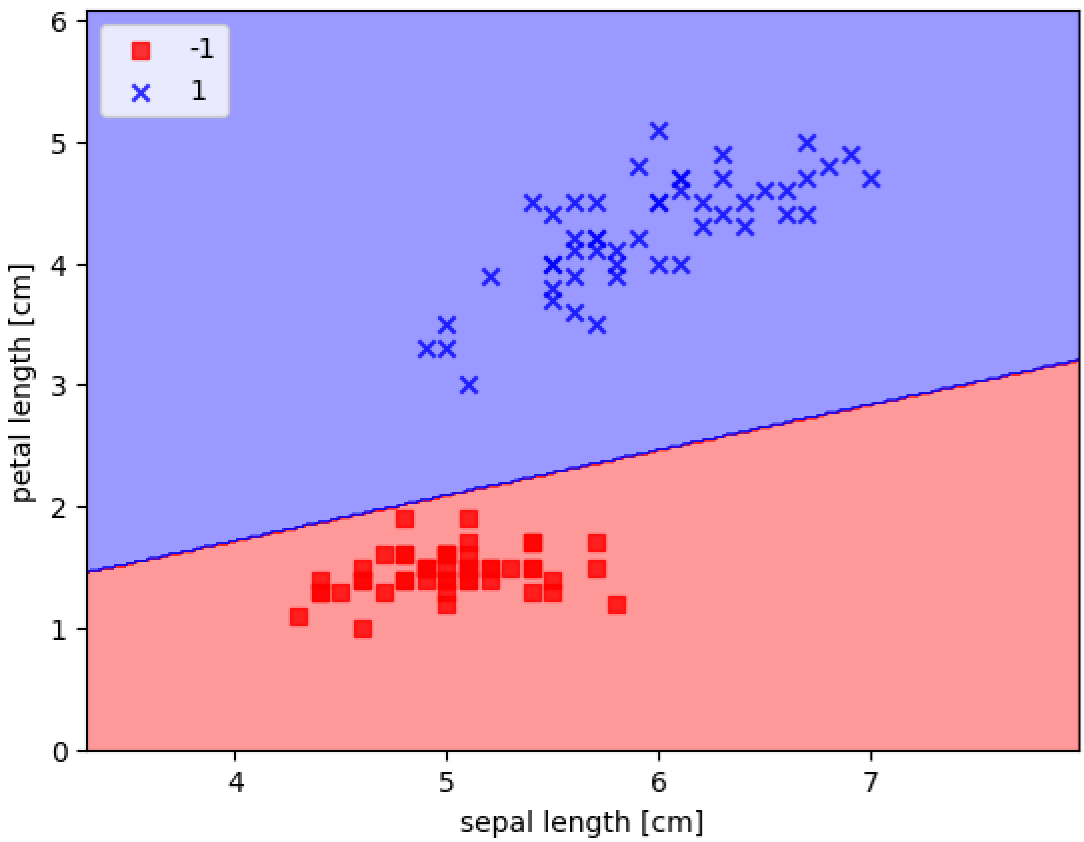
PERCEPTRON

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from perceptron import Perceptron
import pdr


# get the iris data
df =
pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data',
  header = None)

# Plot 100 samples od the data

y = df.iloc[0:100, 4].values
y = np.where(y == 'Iris-setosa', -1, 1)
X = df.iloc[0:100, [0, 2]].values
```

```python
plt.scatter(X[:50, 0], X[:50, 1], color = 'red', marker =
'o', label = 'setosa')
plt.scatter(X[50:100, 0], X[50:100, 1], color = 'blue',
marker = 'x', label = 'versicolor')
plt.xlabel('petal length')
plt.ylabel('sepal length')
plt.legend(loc = 'upper left')
plt.show()

# get the perceptron model
model = Perceptron(eta = 0.1, n_iter = 10)

# train the model
model.fit(X, y)

# plot the training error
plt.plot(range(1, len(model.errors_) + 1), model.errors_,
marker = 'o')
plt.xlabel('Epochs')
plt.ylabel('Number of misclassifications')
plt.show()

# create decision regions
pdr.plot_decision_regions(X, y, classifier = model)
plt.xlabel('sepal length [cm]')
plt.ylabel('petal length [cm]')
plt.legend(loc = 'upper left')
plt.show()
```


setosa
versicolor
sepal length
petal length


Number of misclassifications
Epochs



BACKPROPAGATION ALGORITHM

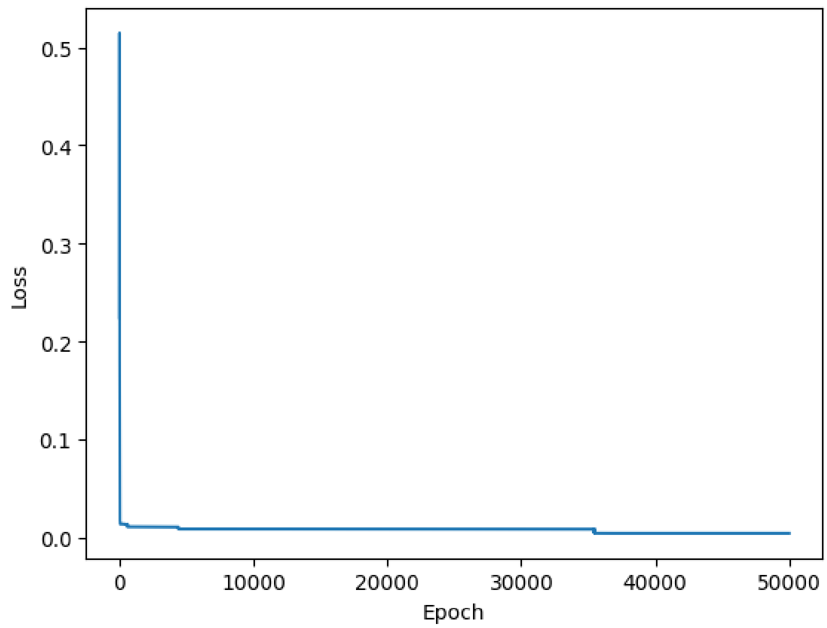
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, roc_curve,
auc
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder,
StandardScaler
```

```
# Load the dataset from the UCI Machine Learning
Repository
data =
pd.read_csv('https://archive.ics.uci.edu/ml/machine-learn
ing-databases/breast-cancer-wisconsin/wdbc.data',
header=None)

# Define the features and target variable
X = data.iloc[:, 2:].values
y = data.iloc[:, 1].values

# Encode the target variable
encoder = LabelEncoder()
y = encoder.fit_transform(y)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=0)

# Standardize the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Define the sigmoid function and its derivative
def sigmoid(x):
    return 1 / (1 + np.exp(-x))

def sigmoid_derivative(x):
    return x * (1 - x)

# Set the number of input, hidden and output nodes
input_nodes = X_train.shape[1]
```

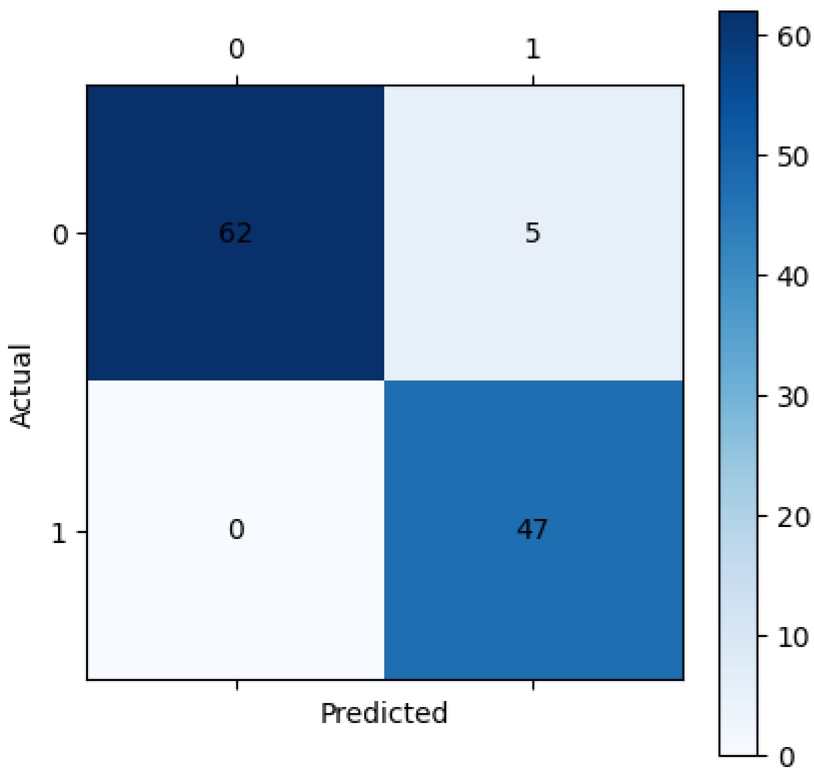
```
hidden_nodes = 4
output_nodes = 1

# Initialize the weights
weights_input_hidden =
np.random.uniform(size=(input_nodes, hidden_nodes))
weights_hidden_output =
np.random.uniform(size=(hidden_nodes, output_nodes))

# Set the learning rate
learning_rate = 0.5

# Initialize a list to store the loss during training
losses = []

# Train the neural network using backpropagation
for epoch in range(50000):
    # Forward pass
    hidden_layer_input = np.dot(X_train,
weights_input_hidden)
    hidden_layer_output = sigmoid(hidden_layer_input)
    output_layer_input = np.dot(hidden_layer_output,
weights_hidden_output)
    output_layer_output = sigmoid(output_layer_input)

    # Calculate the error
    error = y_train.reshape(-1, 1) - output_layer_output

    # Store the mean squared error for this epoch
    losses.append(np.mean(error**2))

    # Backward pass
```

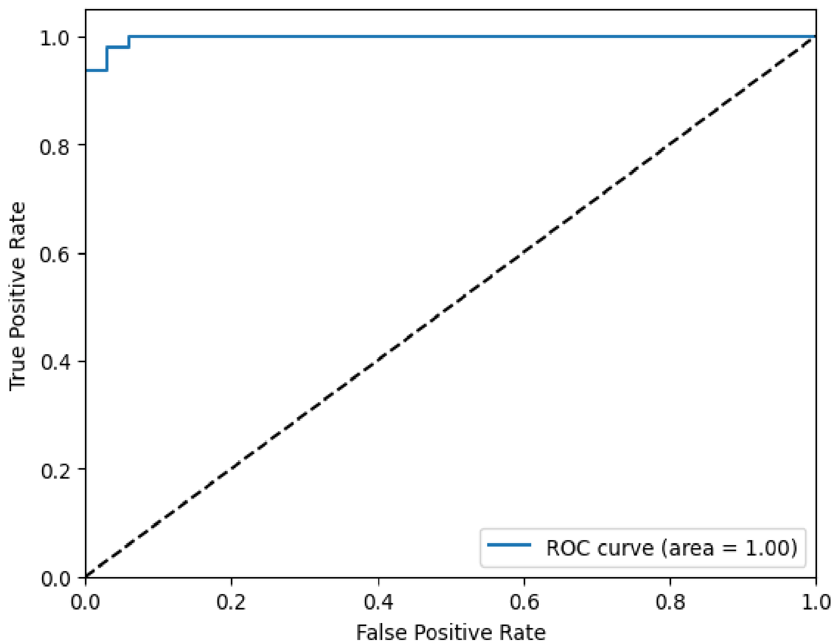
```
    d_output_layer_output = error *
sigmoid_derivative(output_layer_output)
    error_hidden_layer =
d_output_layer_output.dot(weights_hidden_output.T)
    d_hidden_layer_output = error_hidden_layer *
sigmoid_derivative(hidden_layer_output)

    # Update the weights
    weights_hidden_output +=
hidden_layer_output.T.dot(d_output_layer_output) *
learning_rate
    weights_input_hidden +=
X_train.T.dot(d_hidden_layer_output) * learning_rate

# Plot the loss during training
plt.plot(losses)
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show()

# Make predictions on the test set
hidden_layer_input = np.dot(X_test, weights_input_hidden)
hidden_layer_output = sigmoid(hidden_layer_input)
output_layer_input = np.dot(hidden_layer_output,
weights_hidden_output)
output_layer_output = sigmoid(output_layer_input)
y_pred_proba = output_layer_output.flatten()
y_pred = (y_pred_proba > 0.5).astype(int)

# Calculate the accuracy on the test set
accuracy = np.mean(y_pred == y_test)
print(f'Accuracy: {accuracy}')
```

```python
# Plot the confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.matshow(cm, cmap=plt.cm.Blues)
plt.colorbar()
for i in range(cm.shape[0]):
    for j in range(cm.shape[1]):
        plt.text(j, i, cm[i, j], ha='center',
va='center')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# Plot the ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
roc_auc = auc(fpr, tpr)
plt.plot(fpr, tpr, label=f'ROC curve (area =
{roc_auc:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc='lower right')
plt.show()
```



Accuracy: 0.956140350877193





True Positive Rate
False Positive Rate
ROC curve (area = 1.00)
0.0
0.2
0.4
0.6
0.8
1.0