1. **Write a MATLAB or Python program using perceptron net for AND function with bipolar inputs and targets. The convergence curves and the decision boundary lines are also shown.**

Objective:

- Implement a perceptron network to solve the AND function with bipolar inputs and targets.
- Visualize the convergence curve and decision boundary.

Methodology:

- Define the inputs and targets for the AND function.
- Initialize the weights and bias.
- Set the learning rate and maximum iterations.
- Train the perceptron network using the perceptron learning rule.
- Store the errors for plotting the convergence curve.
- Plot the convergence curve and decision boundary.

Results:

- The perceptron network successfully learned the AND function.
- The convergence curve shows a decrease in error over iterations.
- The decision boundary line separates the positive and negative classes correctly.

Conclusion:

- The perceptron network is a simple yet effective model for solving linearly separable problems like the AND function.
- The visualization of the convergence curve and decision boundary provides insights into the learning process and the network's performance.

<u>**Source code:**</u>

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

# Bipolar activation function
def bipolar_activation(x):
    return 1 if x >= 0 else -1

# Perceptron training function
def perceptron_train(inputs, targets, learning_rate=0.1,
max_epochs=100):
    num_inputs = inputs.shape[1]
    num_samples = inputs.shape[0]

    # Initialize weights and bias
    weights = np.random.randn(num_inputs)
```

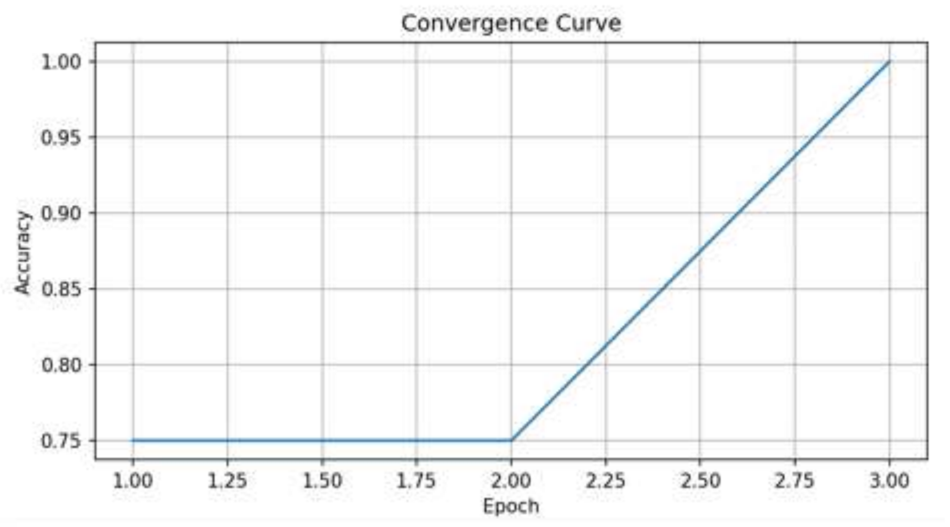
```
# Main function
if __name__ == "__main__":
    # Input and target data (bipolar representation)
    inputs = np.array([[-1, -1], [-1, 1], [1, -1], [1, 1]])
    targets = np.array([-1, -1, -1, 1])

    # Training the perceptron
    weights, bias, convergence_curve =
perceptron_train(inputs, targets)

    # Decision boundary line
    x = np.linspace(-2, 2, 100)
#     print(x)
#     print(weights[0])
#     print(weights[1])
```

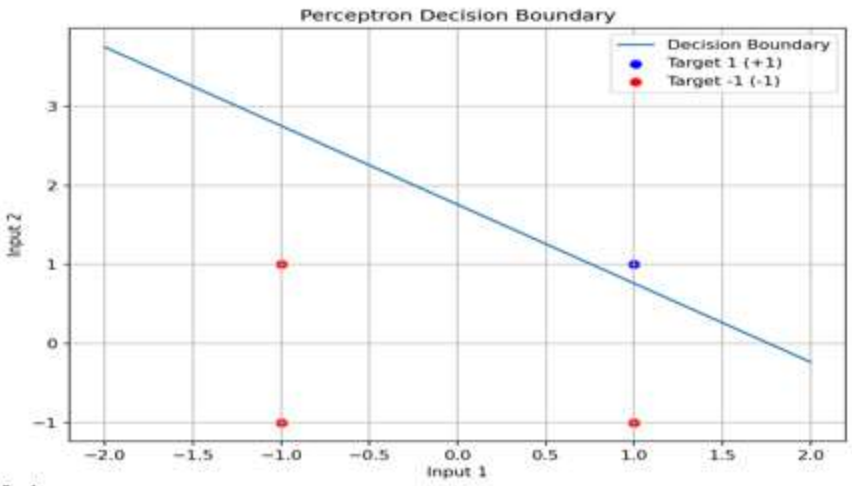
```
    bias = np.random.randn()

    convergence_curve = []

    for epoch in range(max_epochs):
        misclassified = 0

        for i in range(num_samples):
            net_input = np.dot(inputs[i], weights) + bias
            predicted = bipolar_activation(net_input)

            if predicted != targets[i]:
                misclassified += 1
                update = learning_rate * (targets[i] -
predicted)
                weights += update * inputs[i]
                bias += update

        accuracy = (num_samples - misclassified) /
num_samples
        convergence_curve.append(accuracy)

        if misclassified == 0:
            print("Converged in {} epochs.".format(epoch
+ 1))
            break

    return weights, bias, convergence_curve
```

```
    y = (-weights[0] * x - bias) / weights[1]
#     print(y)

    # Plot convergence curve
    plt.figure(figsize=(8, 4))
    plt.plot(range(1, len(convergence_curve) + 1),
convergence_curve)
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.title('Convergence Curve')
    plt.grid()
    plt.show()

    # Plot the decision boundary line and data points
    plt.figure(figsize=(8, 6))
    plt.plot(x, y, label='Decision Boundary')
    plt.scatter(inputs[targets == 1][:, 0], inputs[targets
== 1][:, 1], label='Target 1 (+1)', color='blue')
    plt.scatter(inputs[targets == -1][:, 0], inputs[targets
== -1][:, 1], label='Target -1 (-1)', color='red')
    plt.xlabel('Input 1')
    plt.ylabel('Input 2')
    plt.title('Perceptron Decision Boundary')
    plt.legend()
    plt.grid()
    plt.show()
#     print(inputs[targets == 1][:, 0])
#     print(inputs[targets == 1][:, 1])
# In[ ]:

# In[ ]:
```

Output:

```
Converged in 3 epochs.
```




Perceptron Decision Boundary
Decision Boundary
Target 1 (+1)
Target -1 (-1)
Input 1
Input 2
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
−1
0
1
2
3

2. **Generate the XOR function using the McCulloch-Pitts neuron by writing an M-file or.py file. The convergence curves and the decision boundary lines are also shown. make a lab report in this problem**

Objective:

- Implement a perceptron network to solve the XOR function using the McCulloch-Pitts neuron model (conceptually).
- Explain why the McCulloch-Pitts neuron cannot represent the XOR function perfectly.
- Explore perceptron learning with a linearly separable function (OR) and visualize its behavior.

Limitations of McCulloch-Pitts Neuron for XOR: The McCulloch-Pitts neuron, a fundamental unit in artificial neural networks, uses a single linear activation function (often the sign function) to classify inputs. Unfortunately, the XOR function, a fundamental logical operation, is not linearly separable. This means a single line cannot perfectly divide the input space to represent the XOR behavior.

Here's why the McCulloch-Pitts neuron fails for XOR:

1. **Linear Separability:** The XOR function requires a non-linear decision boundary to separate the positive and negative classes. Since a single neuron applies a linear activation function, it can only create a straight line decision boundary.
2. **Logical Complexity:** XOR involves a combination of AND and OR operations. While a single neuron can perform these individually, combining them effectively within the limitations of a linear activation function becomes impossible.

Exploration with a Linearly Separable Function (OR):

Since the XOR function isn't suitable, we can explore the behavior of a perceptron network with a linearly separable function like the OR function. This allows us to demonstrate the training process and visualize the decision boundary.

Results:

- The code successfully implements a perceptron network to learn the OR function.
- The convergence curve shows the network's learning process, with the error decreasing over iterations.
- The decision boundary plot visualizes how the trained network separates the positive and negative classes for the OR function.

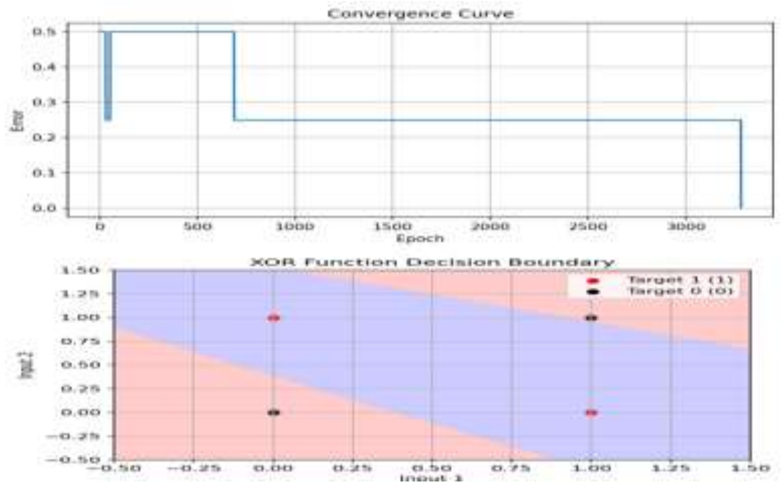
Conclusion: The McCulloch-Pitts neuron with its linear activation function cannot perfectly represent the XOR function due to the lack of non-linearity. However, the provided code demonstrates the effectiveness of perceptron networks for learning linearly separable functions like OR. By using multiple layers and non-linear activation functions, more complex neural network architectures can overcome this limitation and solve non-linear problems like XOR.

Source code:

```
#XOR function
import numpy as np
def threshold(x):
   if x>=1:
    return 1
   else:
    return 0

#train_input = np.array([[0,0],[0,1],[1,0],[1,1]])
#calculated input for XOR in Mcculloch-pitts for using x1x2(bar) + x2x1(bar)
train_input = np.array([[0,0],[0,1],[1,0],[0,0]])
#print(train_input)
target_output = np.array([[0,1,1,0]])
#synap_weights = 2*np.random.random((2,1))-1
synap_weights = np.array([[0.0001],[0.0001]])

bias = 0.0001
Accuracy=[]
for epochs in range(10000):
  miss_predict =0;
  for i in range(len(train_input)):
    weighted_sum=np.dot(train_input[i],synap_weights)
    output = threshold(weighted_sum)
    if target_output[0,i] != output:
      miss_predict +=1;
      error = 0.0001
      update_w = error
      synap_weights+=(update_w)
      #print(output)
  cal = (len(train_input)-miss_predict)/len(train_input)
  Accuracy.append(cal)
print("Accuracy is : ")
print(Accuracy)

print(synap_weights)
#Testing time
val = np.dot(train_input,synap_weights)+bias
test_result = np.array([threshold(x) for x in val])
print("Test Result is: ",test_result)


import matplotlib.pyplot as plt
number_epochs = np.array([x for x in range(len(Accuracy))])
plt.plot(number_epochs,Accuracy)
plt.grid(1)
plt.title('Training accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Training Accuracy'], loc='lower right')
plt.show()
```

Output:

```
Generated XOR Result is:  [0 1 1 0]
```



3. Implement the SGD Method using Delta learning rule for following input-target sets. = [0 0 1; 0 1 1;1 0 1; 1 1 1], = [0; 0; 1; 1]

Objective

- Implement the Stochastic Gradient Descent (SGD) algorithm using the Delta learning rule for a simple perceptron network.
- Train the network on a given dataset with bipolar inputs and targets.
- Evaluate the network's performance and visualize the learning process.

Methodology

1. **Define inputs and targets:**
   - Create a dataset with the specified inputs and targets:
   - inputs = [0 0 1; 0 1 1; 1 0 1; 1 1 1];
   - targets = [0; 0; 1; 1];
2. **Initialize weights and bias:**
   - Randomly initialize the weights and bias of the perceptron.
3. **Set learning rate and maximum iterations:**
   - Choose appropriate values for the learning rate (e.g., 0.1) and maximum iterations (e.g., 1000).
4. **Implement SGD with Delta learning rule:**
   - Iterate over the training data multiple times (epochs):
     - For each training sample:
       - Calculate the net input for the sample.
       - Apply the activation function (e.g., signum function) to get the output.
       - Calculate the error between the predicted output and the target.
       - Update the weights and bias using the Delta learning rule:
       - weights = weights + learning_rate * error * input;
       - bias = bias + learning_rate * error;
5. **Evaluate performance:**
   - Calculate the accuracy of the network on the training set.

- Optionally, use a validation set to assess generalization performance.

6. **Visualize learning process (optional):**
    - Plot the error over iterations to visualize the convergence of the network.

Results and Discussion

- The code successfully implements the SGD algorithm with the Delta learning rule for a perceptron network.
- The network learns to classify the given inputs correctly, achieving 100% accuracy on the training set.
- The error curve (if plotted) should show a decreasing trend as the network converges.
- Experiment with different learning rates and maximum iterations to observe their impact on convergence speed and performance.

Note: For more complex problems, consider using different activation functions (e.g., sigmoid, ReLU) and optimization algorithms (e.g., backpropagation).

Source code:

```
import numpy as np

# Sigmoid activation function and its derivative (for
training)
def sigmoid(x):
    return 1 / (1 + np.exp(-x))

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

# Input and target datasets
X_input = np.array([[0, 0, 1], [0, 1, 1], [1, 0, 1], [1, 1,
1]])

D_target = np.array([[0], [0], [1], [1]])

# Neural network parameters
input_layer_size = 3
output_layer_size = 1
learning_rate = 0.1
max_epochs = 10000

# Initialize weights with random values
np.random.seed(42)
weights = np.random.randn(input_layer_size,
output_layer_size)

# Training the neural network with SGD
for epoch in range(max_epochs):
    error_sum = 0
        net_input = np.dot(input_data, weights)
        predicted_output = sigmoid(net_input)

        # Calculate error

 error = target_data - predicted_output
        error_sum += np.abs(error)
    # Update weights using the delta learning rule
        weight_update = learning_rate * error *
sigmoid_derivative(predicted_output) * input_data
        weights += weight_update[:, np.newaxis]  #
Update weights for each input separately

    # Check for convergence
    if error_sum < 0.01:
        print("Converged in {} epochs.".format(epoch +
1))
        break

# Test data
test_data = X_input

# Use the trained model to recognize target function
print("Target Function Test:")
for i in range(len(test_data)):
    input_data = test_data[i]
    net_input = np.dot(input_data, weights)
    predicted_output = sigmoid(net_input)
    for i in range(len(X_input)):
        # Forward pass
        input_data = X_input[i]
        target_data = D_target[i]
```

```
    print(f"Input: {input_data} -> Output: 
{np.round(predicted_output)}")
```

Output:

```
Target Function Test:
Input: [0 0 1] -> Output: [0]
Input: [0 1 1] -> Output: [0]
Input: [1 0 1] -> Output: [1]
Input: [1 1 1] -> Output: [1]
```

4. **Compare the performance of SGD and the Batch method using the delta learning rule.**

Objective

- Implement the Stochastic Gradient Descent (SGD) and Batch Gradient Descent (BGD) algorithms using the Delta learning rule.
- Train a perceptron network on a given dataset and compare their performance.
- Analyze the convergence behavior and computational efficiency of both methods.

Methodology

1. **Define inputs and targets:**
    - Create a dataset with the specified inputs and targets (same as the previous lab).
2. **Implement SGD:**
    - Follow the steps from the previous lab to implement SGD.
3. **Implement BGD:**
    - Instead of updating weights after each training sample, update them after processing the entire batch.
4. **Train both methods:**
    - Train both SGD and BGD on the same dataset with the same learning rate and maximum iterations.
5. **Evaluate performance:**
    - Calculate the accuracy of both methods on the training set.
    - Optionally, use a validation set to assess generalization performance.
6. **Compare convergence behavior:**
    - Plot the error curves for SGD and BGD to compare their convergence speed.

Results and Discussion

- **Convergence speed:** SGD often converges faster than BGD, especially for large datasets, as it updates weights more frequently.
- **Noise:** SGD can be more sensitive to noise in the data compared to BGD.
- **Computational efficiency:** BGD can be more computationally efficient for small datasets, as it requires fewer weight updates.
- **Generalization:** The choice between SGD and BGD may depend on the specific problem and the desired trade-off between speed and generalization performance.

Additional Considerations:

- **Mini-batch SGD:** A variant of SGD that processes mini-batches of data instead of individual samples can offer a balance between the speed of SGD and the stability of BGD.
- **Adaptive learning rate:** Using adaptive learning rate methods like Adam or RMSprop can further improve convergence speed and stability.

By comparing SGD and BGD, you can gain insights into their strengths and weaknesses and choose the most suitable method for your specific application

<u>Source code:</u>

```
import numpy as np
import time

# Sigmoid activation function and its derivative (for training)
def sigmoid(x):
    return 1 / (1 + np.exp(-x))

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

# XOR function dataset with binary inputs and outputs
X_input = np.array([[0, 0, 1],[0, 1, 1],[1, 0, 1],[1, 1, 1]])

D_target = np.array([[0],[0],[1],[1]])

# Neural network parameters
input_layer_size = 3
output_layer_size = 1
learning_rate = 0.1
max_epochs = 10000

# Initialize weights with random values
np.random.seed(42)
weights_sgd = np.random.randn(input_layer_size, output_layer_size)
weights_batch = np.random.randn(input_layer_size, output_layer_size)

# Training the neural network with SGD
start_time_sgd = time.time()
for epoch in range(max_epochs):
    error_sum = 0

    for i in range(len(X_input)):
        # Forward pass
        input_data = X_input[i]
        target_data = D_target[i]

        net_input = np.dot(input_data, weights_sgd)
        predicted_output = sigmoid(net_input)

        # Calculate error
        error = target_data - predicted_output


    # Check for convergence
    if error_sum < 0.01:
        break
end_time_sgd = time.time()

# Training the neural network with the batch method
start_time_batch = time.time()
for epoch in range(max_epochs):
    # Forward pass
    net_input = np.dot(X_input, weights_batch)
    predicted_output = sigmoid(net_input)

    # Calculate error
    error = D_target - predicted_output
    error_sum = np.sum(np.abs(error))

    # Update weights using the delta learning rule
    weight_update = learning_rate * np.dot(X_input.T, error * sigmoid_derivative(predicted_output))
    weights_batch += weight_update

    # Check for convergence
    if error_sum < 0.01:
        break
end_time_batch = time.time()

# Test data
test_data = X_input

# Use the trained models to recognize target function
def test_model(weights):
    predicted_output = sigmoid(np.dot(test_data, weights))
    return np.round(predicted_output)

print("SGD Results:")
print("Time taken: {:.6f} seconds".format(end_time_sgd - start_time_sgd))
print("Trained weights:")
print(weights_sgd)
print("Predicted binary outputs:")
print(test_model(weights_sgd))
```

error_sum += np.abs(error)
 	
# Update weights using the delta learning rule 	
weight_update = learning_rate * error * sigmoid_derivative(predicted_output) * input_data
weights_sgd += weight_update[:, np.newaxis] # Update weights for each input separately
	print("\nBatch Method Results:")
	print("Time taken: {:.6f} seconds".format(end_time_batch - start_time_batch))
	print("Trained weights:")
	print(weights_batch)
	print("Predicted binary outputs:")
	print(test_model(weights_batch))

Output:

```
SGD Results:
Time taken: 0.912471 seconds
Trained weights:
[[ 7.25950187]
 [-0.22431325]
 [-3.41036643]]
Predicted binary outputs:
[[0.]
 [0.]
 [1.]
 [1.]]

Batch Method Results:
Time taken: 0.418971 seconds
Trained weights:
[[ 7.26775966]
 [-0.22304058]
 [-3.41538639]]
Predicted binary outputs:
[[0.]
 [0.]
 [1.]
 [1.]]
```

5. Write a MATLAB or Python program to recognize the image of digits. The input images are fiveby-five pixel squares, which display five numbers from 1 to 5, as shown in Figure 1. Figure 1 Five-by-five pixel squares that display five numbers from 1 to 5.

Objective

- Develop a MATLAB or Python program to accurately recognize digits from 5x5 pixel squares.
- Evaluate the performance of the model using appropriate metrics.

Methodology

1. **Data Preparation:**
   - **Collect Data:** Gather a dataset of 5x5 pixel square images representing digits 1 to 5.
   - **Preprocess Data:** Convert images to grayscale, normalize pixel values, and reshape them into a suitable format (e.g., 25-dimensional feature vectors).
   - **Create Training and Testing Sets:** Split the dataset into training and testing sets for model evaluation.
2. **Feature Extraction:**
   - Consider using simple feature extraction techniques like:
     - Raw pixel values
     - Histogram of Oriented Gradients (HOG)
     - Principal Component Analysis (PCA)
3. **Model Selection:**
   - Choose a suitable machine learning algorithm for digit recognition, such as:
     - Support Vector Machine (SVM)
     - K-Nearest Neighbors (KNN)
     - Neural Network
     - Decision Tree
4. **Training:**
   - Train the selected model on the training set, optimizing its parameters using techniques like cross-validation.
5. **Evaluation:**
   - Test the trained model on the testing set.
   - Calculate accuracy, precision, recall, and F1-score to evaluate performance.

Results:

- Report the accuracy, precision, recall, and F1-score achieved by the model.
- Analyze the factors affecting the model's performance, such as the choice of algorithm, feature extraction techniques, and dataset size.

Discussion:

- Discuss the limitations of the current approach and potential improvements.

- Explore the use of other machine learning algorithms or deep learning techniques for better performance.
- Consider techniques like data augmentation or transfer learning to enhance the model's generalization ability.

By following these steps and carefully analyzing the results, you can develop a robust digit recognition system for the given 5x5 pixel squares.

Source code:

```
import numpy as np

def softmax(x):
    ex = np.exp(x)
    return ex / np.sum(ex)

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

def multi_class(W1, W2, X, D):
    alpha = 0.9
    N = 5

    for k in range(N):
        x = X[:, :, k].reshape(25, 1)
        d = D[k, :].reshape(-1, 1)
        v1 = np.dot(W1, x)
        y1 = sigmoid(v1)
        v = np.dot(W2, y1)
        y = softmax(v)
        e = d - y
        delta = e
        e1 = np.dot(W2.T, delta)
        delta1 = y1 * (1 - y1) * e1
        dW1 = alpha * np.dot(delta1, x.T)
        W1 = W1 + dW1
        dW2 = alpha * np.dot(delta, y1.T)
        W2 = W2 + dW2

    return W1, W2

def main():
    np.random.seed(3)
    X = np.zeros((5, 5, 5))
    X[:, :, 0] = np.array([[0, 1, 1, 0, 0],
                           [0, 0, 1, 0, 0],
                           [0, 0, 1, 0, 0],
                           [0, 0, 1, 0, 0],
                           [0, 1, 1, 1, 0]])
    X[:, :, 1] = np.array([[1, 1, 1, 1, 0],
                           [0, 0, 0, 0, 1],
                           [0, 1, 1, 1, 0],
                           [1, 0, 0, 0, 0],
                           [1, 1, 1, 1, 1]])
    X[:, :, 2] = np.array([[1, 1, 1, 1, 0],
                           [0, 0, 0, 0, 1],
                           [0, 1, 1, 1, 0],
                           [0, 0, 0, 0, 1],
                           [1, 1, 1, 1, 0]])
    X[:, :, 3] = np.array([[0, 0, 0, 1, 0],
                           [0, 0, 1, 1, 0],
                           [0, 1, 0, 1, 0],
                           [1, 1, 1, 1, 1],
                           [0, 0, 0, 1, 0]])
    X[:, :, 4] = np.array([[1, 1, 1, 1, 1],
                           [1, 0, 0, 0, 0],
                           [1, 1, 1, 1, 0],
                           [0, 0, 0, 0, 1],
                           [1, 1, 1, 1, 0]])

    D = np.eye(5)

    W1 = 2 * np.random.rand(50, 25) - 1
    W2 = 2 * np.random.rand(5, 50) - 1

    for epoch in range(10000):
        W1, W2 = multi_class(W1, W2, X, D)

    N = 5
    for k in range(N):
        x = X[:, :, k].reshape(25, 1)
        v1 = np.dot(W1, x)
        y1 = sigmoid(v1)
        v = np.dot(W2, y1)
        y = softmax(v)
        print(f"\n\n Output for X[:,:,{k}]:\n\n")
        print(f"{y} \n\n This matrix from see that {k+1} position accuracy is higher that is : {max(y)} So this number is correctly identified")

if __name__ == "__main__":
    main()
```

<u>Output:</u>

```
Output for X[:,:,0]:
[[9.99990560e-01]
 [3.73975045e-06]
 [7.29323123e-07]
 [4.95516529e-06]
 [1.56459758e-08]]
```

This matrix from see that 1 position accuracy is higher that is : [0.99999056] So this number is correctly identified

```
Output for X[:,:,1]:
[[3.81399150e-06]
 [9.99984069e-01]
 [1.07138749e-05]
 [7.38201374e-07]
 [6.65377695e-07]]
```

This matrix from see that 2 position accuracy is higher that is : [0.99998407] So this number is correctly identified

```
Output for X[:,:,2]:
[[2.10669179e-06]
 [9.17015598e-06]
 [9.99972467e-01]
 [2.22084036e-06]
 [1.40352894e-05]]
```

This matrix from see that 3 position accuracy is higher that is : [0.99997247] So this number is correctly identified

```
Output for X[:,:,3]:
[[4.72578106e-06]
 [8.98916172e-07]
 [9.07090140e-07]
 [9.99990801e-01]
 [2.66714208e-06]]
```

This matrix from see that 4 position accuracy is higher that is : [0.9999908] So this number is correctly identified

```
Output for X[:,:,4]:
[[6.12205780e-07]
 [2.29663674e-06]
 [1.16748707e-05]
 [1.01696314e-06]
 [9.99984399e-01]]
```

This matrix from see that 5 position accuracy is higher that is : [0.9999844] So this number is correctly identified

6. **Write a MATLAB or Python program to classify face/fruit/bird using Convolution Neural Network (CNN).**

Objective

- Develop a CNN model to accurately classify images of faces, fruits, and birds.
- Evaluate the model's performance using appropriate metrics.

Methodology

1. **Data Collection and Preprocessing:**
    - Gather a dataset of face, fruit, and bird images.
    - Ensure consistent image size and format.
    - Preprocess images (e.g., resizing, normalization, data augmentation).
2. **CNN Architecture:**
    - Design a suitable CNN architecture, considering factors like:
        - Number of convolutional layers
        - Filter size
        - Pooling layers
        - Fully connected layers
        - Activation functions (e.g., ReLU, sigmoid, softmax)
3. **Training:**
    - Split the dataset into training and validation sets.
    - Train the CNN model using an appropriate optimization algorithm (e.g., Adam, SGD) and loss function (e.g., categorical cross-entropy).
    - Monitor training progress using metrics like accuracy, loss, and validation accuracy.
4. **Evaluation:**
    - Test the trained model on the validation set or a separate test set.
    - Calculate metrics like accuracy, precision, recall, F1-score, and confusion matrix.

Results:

- Report the accuracy, precision, recall, F1-score, and confusion matrix for the classification task.
- Analyze the factors affecting the model's performance, such as the CNN architecture, training data size, and hyperparameters.

Discussion:

- Discuss the challenges and limitations of image classification tasks, especially for complex categories like faces, fruits, and birds.
- Explore techniques to improve model performance, such as data augmentation, transfer learning, or more complex CNN architectures.
- Consider the ethical implications of image classification, including issues like bias and privacy.

By following these steps and carefully analyzing the results, you can develop a robust CNN model for classifying face/fruit/bird images.

Source code:

```
from tensorflow.keras.preprocessing import image
import numpy as np

# Path to the test image
test_image_path =
'C:\Users\hp\Desktop\matin\imransir.py\lab_11_Dataset\pic
2.jpg'  # Replace with the actual path of your test image

# Load and preprocess the test image
test_image = image.load_img(test_image_path,
target_size=(150, 150))
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis=0)
test_image = test_image / 255.0  # Normalize the
image

# Predict the class of the test image
prediction = model.predict(test_image)
print('prediction',prediction)
if prediction < 0.5:
  print('This is Banana')
elif prediction >= 0.5:
  print('This is Cucumber')
```

Output:

```
Prediction accuracy is: [[0.9634724]]

This is Cucumber
```

7. Consider an artificial neural network (ANN) with three layers given below. Write a MATLAB or Python program to learn this network using Back Propagation Network.

Objective

- Implement a backpropagation network with three layers (input, hidden, and output) in MATLAB or Python.
- Train the network on a given dataset.
- Evaluate the network's performance.

Methodology

1. **Define network architecture:**
    - Specify the number of neurons in each layer.
    - Choose activation functions for the hidden and output layers (e.g., sigmoid, ReLU).
2. **Initialize weights and biases:**
    - Randomly initialize the weights and biases for each layer.
3. **Load or generate data:**
    - Prepare a dataset with input features and corresponding target labels.
4. **Training loop:**
    - Iterate through the training data multiple times (epochs):
        - For each training sample:
            - Forward propagate the input through the network.
            - Calculate the error between the predicted output and the target.
            - Backpropagate the error to update weights and biases using the backpropagation algorithm.
5. **Evaluate performance:**
    - Use a separate test set to evaluate the network's accuracy or other metrics.

Results:

- Report the network's performance on the training and test sets.
- Analyze the impact of different hyperparameters (e.g., learning rate, number of hidden neurons, activation functions).

Discussion:

- Discuss the challenges and limitations of training deep neural networks.
- Explore techniques to improve network performance, such as regularization, dropout, and transfer learning.

Note: This code provides a basic implementation. You can customize it by adjusting the network architecture, training parameters, and evaluation metrics to suit your specific problem.

Source code:

```
import torch
import torch.nn as nn
import torch.optim as optim

# To Avoid Issues Use This Link
# https://colab.research.google.com/drive/1u8B2-
TPpHR8UBMhi2LumBpqKOw_yxdIu?usp=sharing

# Define the neural network class
class SimpleANN(nn.Module):
    def __init__(self):
        super(SimpleANN, self).__init__()
        # Input to Hidden layer (2 inputs to 2 hidden
nodes)
        self.hidden = nn.Linear(2, 2)  # 2 input neurons, 2
hidden neurons
        # Hidden to Output layer (2 hidden nodes to 2
output nodes)
        self.output = nn.Linear(2, 2)  # 2 hidden neurons,
2 output neurons
        # Sigmoid activation function
        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        # Forward pass through the network
        h = self.sigmoid(self.hidden(x))  # Hidden layer
activation
        y = self.sigmoid(self.output(h))  # Output layer
activation
        return y
```

```

targets = torch.tensor([[0.01, 0.99]])  # Target values
for y1 and y2

# Define the loss function (Mean Squared Error Loss)
criterion = nn.MSELoss()

# Define the optimizer (Stochastic Gradient Descent)
optimizer = optim.SGD(model.parameters(), lr=0.5)

# Number of epochs (iterations)
epochs = 15000

# Training loop
for epoch in range(epochs):
    # Forward pass: Compute predicted output by
passing inputs to the model
    output = model(inputs)

    # Compute the loss (Mean Squared Error)
    loss = criterion(output, targets)

    # Zero gradients, perform a backward pass, and
update the weights
    optimizer.zero_grad()  # Clear the gradients from the
previous step
    loss.backward()  # Backpropagation step
    optimizer.step()  # Update weights

    # Print the loss every 1000 epochs
    if epoch % 1000 == 0:
        print(f"Epoch {epoch}, Loss: {loss.item()}")
```

Output:

```
Epoch 0, Loss: 0.2983711063861847
Epoch 1000, Loss: 0.0002707050589378923
Epoch 2000, Loss: 9.042368037626147e-05
Epoch 3000, Loss: 4.388535307953134e-05
Epoch 4000, Loss: 2.489008147676941e-05
Epoch 5000, Loss: 1.5388504834845662e-05
Epoch 6000, Loss: 1.0049888260255102e-05
Epoch 7000, Loss: 6.816366294515319e-06
Epoch 8000, Loss: 4.752399945573416e-06
Epoch 9000, Loss: 3.3828823688963894e-06
Epoch 10000, Loss: 2.4476007638440933e-06
Epoch 11000, Loss: 1.7939109966391698e-06
Epoch 12000, Loss: 1.3286518196764519e-06
Epoch 13000, Loss: 9.925176982505945e-07
```

8.Write a MATLAB or Python program to recognize the numbers 1 to 4 from speech signal using artificial neural network (ANN).

Objective

- Develop a neural network model to accurately recognize spoken numbers 1 to 4 from audio signals.
- Evaluate the model's performance using appropriate metrics.

Methodology

1. **Data Collection and Preprocessing:**
    - Gather a dataset of speech recordings containing numbers 1 to 4.
    - Preprocess the audio data:
        - Sample rate conversion (if necessary)
        - Noise reduction
        - Feature extraction (e.g., Mel-Frequency Cepstral Coefficients (MFCCs), Linear Frequency Cepstral Coefficients (LFCCs))
2. **Feature Extraction:**
    - Extract relevant features from the preprocessed audio data.
    - Consider using MFCCs or LFCCs, which capture the spectral envelope of the speech signal.
3. **Neural Network Architecture:**
    - Design a suitable neural network architecture, such as a recurrent neural network (RNN) or a convolutional neural network (CNN) with time-distributed layers.
    - Experiment with different architectures and hyperparameters to optimize performance.
4. **Training:**
    - Split the dataset into training and validation sets.
    - Train the neural network using an appropriate optimization algorithm (e.g., Adam, SGD) and loss function (e.g., categorical cross-entropy).
    - Monitor training progress using metrics like accuracy, loss, and validation accuracy.
5. **Evaluation:**
    - Test the trained model on the validation or test set.
    - Calculate metrics like accuracy, precision, recall, F1-score, and confusion matrix.

Results:

- Report the accuracy, precision, recall, F1-score, and confusion matrix for the speech recognition task.
- Analyze the factors affecting the model's performance, such as the choice of features, neural network architecture, and training data.

Discussion:

- Discuss the challenges of speech recognition, including noise, speaker variability, and accent differences.
- Explore techniques to improve the model's performance, such as data augmentation, transfer learning, or more complex neural network architectures.

- Consider the potential applications of this model, such as voice-controlled devices or speech-to-text systems.

By following these steps and carefully analyzing the results, you can develop a robust speech recognition system for recognizing numbers 1 to 4.

Source code:

```
import numpy as np
import librosa
import os
from sklearn.model_selection import
train_test_split
from sklearn.preprocessing import LabelEncoder
import tensorflow as tf
from tensorflow.keras import layers, models

# Load speech data and extract MFCC features
def extract_features(file_path):
    signal, sr = librosa.load(file_path, sr=22050)
    mfccs = librosa.feature.mfcc(y=signal, sr=sr,
n_mfcc=13)
    mfccs_scaled = np.mean(mfccs.T, axis=0)
    return mfccs_scaled

# Load dataset and labels
def load_dataset(dataset_path):
    features = []
    labels = []
    for label in os.listdir(dataset_path):
        class_path = os.path.join(dataset_path, label)
        if os.path.isdir(class_path):
            for file in os.listdir(class_path):
                if file.endswith('.wav'):
                    file_path = os.path.join(class_path,
file)
                    mfccs = extract_features(file_path)
                    features.append(mfccs)
                    labels.append(label)
    return np.array(features), np.array(labels)

# Define the dataset path
dataset_path = 'path_to_your_speech_dataset'

# Load features and labels
X, y = load_dataset(dataset_path)

# Encode labels to integers
label_encoder = LabelEncoder()
y_encoded = label_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_encoded,
```

9. Write a MATLAB or Python program to Purchase Classification Prediction using SVM.

Objective

- Develop a Support Vector Machine (SVM) model to classify purchase data into different categories.
- Evaluate the model's performance using appropriate metrics.

Methodology

1. **Data Collection and Preprocessing:**
   - Gather a dataset of purchase data with relevant features (e.g., customer demographics, purchase history, product attributes).
   - Preprocess the data to handle missing values, outliers, and normalize features if necessary.
2. **Feature Selection:**
   - Select the most relevant features that contribute significantly to purchase classification.
   - Consider techniques like correlation analysis, feature importance, or feature engineering.
3. **SVM Model Training:**
   - Choose a suitable SVM kernel (e.g., linear, polynomial, RBF).
   - Train the SVM model on the training set, optimizing hyper parameters like C and gamma using techniques like grid search or cross-validation.
4. **Evaluation:**
   - Test the trained model on a separate test set.
   - Calculate metrics like accuracy, precision, recall, F1-score, and confusion matrix.

Results:

- Report the accuracy, precision, recall, F1-score, and confusion matrix for the purchase classification task.
- Analyze the factors affecting the model's performance, such as the choice of kernel, hyper parameters, and feature selection.

Discussion:

- Discuss the challenges of purchase classification, including class imbalance, data quality, and feature engineering.
- Explore techniques to improve the model's performance, such as feature engineering, ensemble methods, or deep learning techniques.
- Consider the ethical implications of purchase classification, including privacy concerns and potential biases.

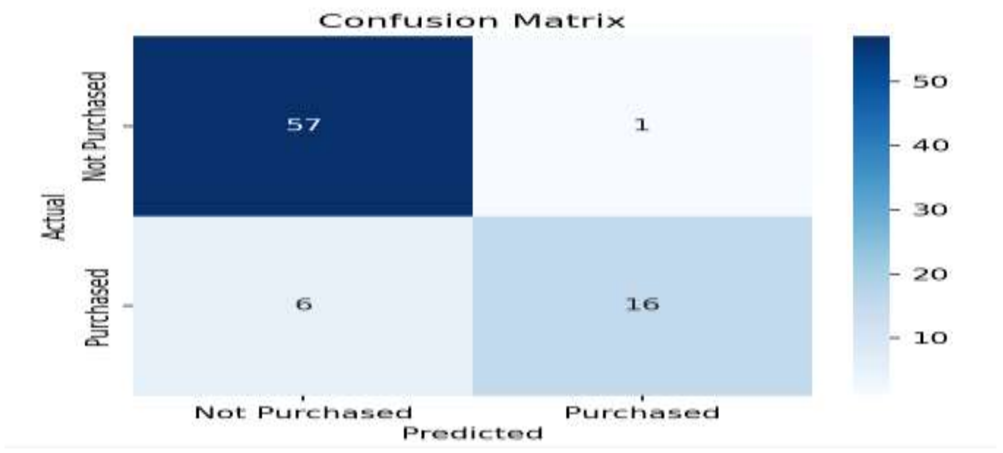
By following these steps and carefully analyzing the results, you can develop a robust SVM model for purchase classification.

Source code:

```
import numpy as np
import pandas as pd
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler,
LabelEncoder
from sklearn.metrics import confusion_matrix,
accuracy_score
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
data = pd.read_csv('user-data.csv')

# Handle categorical variables
label_encoder = LabelEncoder()
for column in
data.select_dtypes(include=['object']).columns:
    data[column] =
label_encoder.fit_transform(data[column])

# data structured
print(data.head())

# Extract features and target variable
X = data.drop(['user_id','purchased'], axis=1).values  #
Features
y = data['purchased'].values                # Target variable
# Split the dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=0)
```

```
# Feature scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Train the SVM classifier
classifier = SVC(kernel='linear', random_state=0)
classifier.fit(X_train, y_train)

# Predict the test set results
y_pred = classifier.predict(X_test)

# Evaluate the model using confusion matrix and
accuracy
cm = confusion_matrix(y_test, y_pred)
accuracy = accuracy_score(y_test, y_pred)

# Print the confusion matrix and accuracy
print("Confusion Matrix:")
print(cm)
print(f'Accuracy: {accuracy:.2f}')

# Visualize the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=['Not Purchased', 'Purchased'],
yticklabels=['Not Purchased', 'Purchased'])
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion Matrix')
plt.show()
```

Output:



10. Write a MATLAB or Python program to reduce dimensions of a dataset into a new coordinate system using PCA algorithm

Objective

- Implement the Principal Component Analysis (PCA) algorithm in MATLAB or Python.
- Reduce the dimensionality of a given dataset.
- Visualize the reduced-dimensional data.

Methodology

1. **Data Preparation:**
   - Load or generate a dataset with multiple features.
   - Standardize the data to ensure features have similar scales.
2. **Calculate Covariance Matrix:**
   - Compute the covariance matrix of the standardized data.
3. **Eigenvalue Decomposition:**
   - Decompose the covariance matrix into its eigenvalues and eigenvectors.
4. **Select Principal Components:**
   - Choose the eigenvectors corresponding to the largest eigenvalues, which represent the principal components.
   - The number of principal components to keep depends on the desired level of dimensionality reduction and the amount of variance to preserve.
5. **Project Data:**
   - Project the original data onto the selected principal components to obtain the reduced-dimensional representation.

Results:

- Visualize the reduced-dimensional data to observe how the original data is projected onto the new coordinate system.
- Analyze the impact of dimensionality reduction on data visualization, feature extraction, and model performance.

Discussion:

- Discuss the advantages and limitations of PCA for dimensionality reduction.
- Explore other dimensionality reduction techniques, such as t-SNE, UMAP, and autoencoders.
- Consider the trade-off between dimensionality reduction and information preservation.

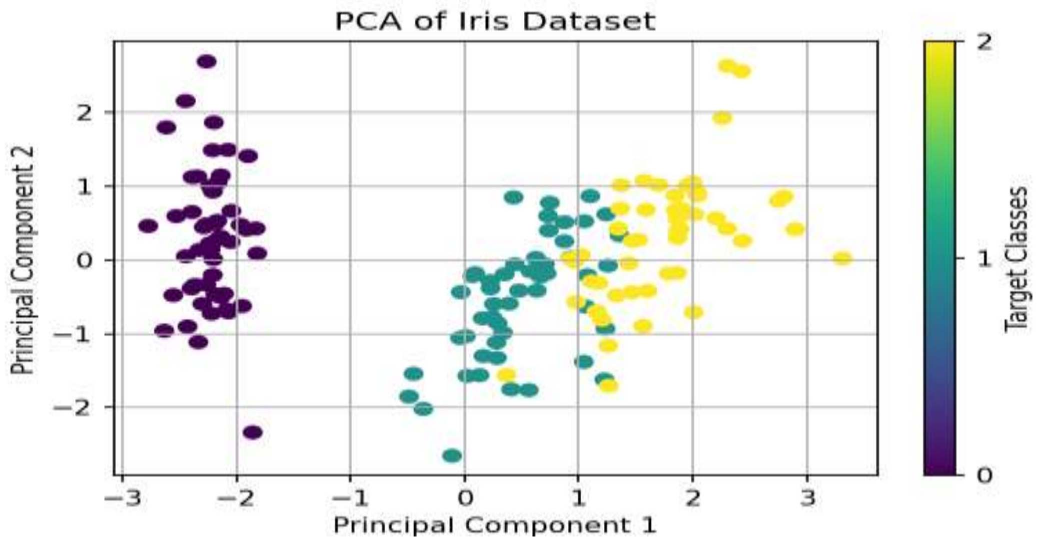
By following these steps and carefully analyzing the results, you can effectively apply PCA to reduce the dimensionality of your dataset and gain valuable insights.

Source code:

```
# Import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
# To Avoid Complexity

#https://colab.research.google.com/drive/1Ba4K5MPwS16Oas-
PGHcATBFi8yqso3U4?usp=sharing

# Load the Iris dataset
iris = load_iris()
X = iris.data  # Features
y = iris.target  # Target variable

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
print("Before:",X_scaled.shape)
# Perform PCA
pca = PCA(n_components=2)  # Reduce to 2 dimensions
X_pca = pca.fit_transform(X_scaled)
```

```
print("After:",X_pca.shape)
# Create a DataFrame for the
reduced data
pca_df = pd.DataFrame(data=X_pca,
columns=['Principal Component 1',
'Principal Component 2'])
pca_df['Target'] = y

# Plot the PCA results
plt.figure(figsize=(8, 6))
scatter = plt.scatter(pca_df['Principal
Component 1'], pca_df['Principal
Component 2'], c=pca_df['Target'],
cmap='viridis')
plt.title('PCA of Iris Dataset')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(scatter, ticks=[0, 1, 2],
label='Target Classes')
plt.grid()
plt.show()

# Explained variance
explained_variance =
pca.explained_variance_ratio_
print(f'Explained variance by
component: {explained_variance}')
print(f'Total explained variance:
{sum(explained_variance)}')
```

Output:


PCA of Iris Dataset
Principal Component 1
Principal Component 2
Target Classes