(A)

Source Code: human-detector-awg297.py

HOG Printout Files:

crop001045b_HOG.txt crop001278a_HOG.txt

(B)

Instructions:

Compile and run the provided .py Python Script.

Upon running the program:

- All of the training and test images will load in
- The neural network will train
- The test images will be classified
- The classification results are printed out

The number of training epochs can be modified by adjusting the parameter given to the function train_network that is called in the main part of the program. The training rate can be be adjusted by adjusting the global variable "train_rate".

(C)

How did you initialize the weight values of the network?

I initialized each weight as a unique random float in the range [0,1), using a numpy random number generator (numpy.random.rand). In this specific neural network, there are [500][7524] weights connecting the input and hidden layer, and [500] weights connecting the hidden layer and output layer.

How many iterations (or epochs) through the training data did you peform?

I performed 150 epochs of training on the neural network, with a training rate of 0.05.

How did you decide when to stop training?

I decided to stop training when the **average error** for a given epoch changed minimally from one iteration to the next. This was a trial and error based approach, adjusting number of epochs, as well as experimenting with training rate, to find the optimal results. When I classified test images on the trained network, obviously a high accuracy rate further validated that my network had received sufficient training.

Based on the output value of the output neuron, how did you decide on how to classify the input image into human or not-human?

If the output value for a given test image was >= 0.5, I classified it as a human. If the output value < 0.5, I classified it as no-human.

(D)

Output neuron results:

Test Image	Output value	Classification
crop_000010b	0.5128826521843262	Human (1)
crop001008b	0.9730568125790874	Human(1)
crop001028a	0.6174900652193422	Human(1)
crop001045b	0.5200295952958314	Human (1)
crop001047b	0.07970313572184756	No Human (0)
00000053a_cut	0.224412223875482	No Human (0)
00000062a_cut	0.14147547474238112	No Human (0)
00000093a_cut	0.03259658278426859	No Human (0)
no_personno_bike_213_cut	0.9688568795203464	Human(1)
no_personno_bike_247_cut	0.010114113644258946	No Human (0)

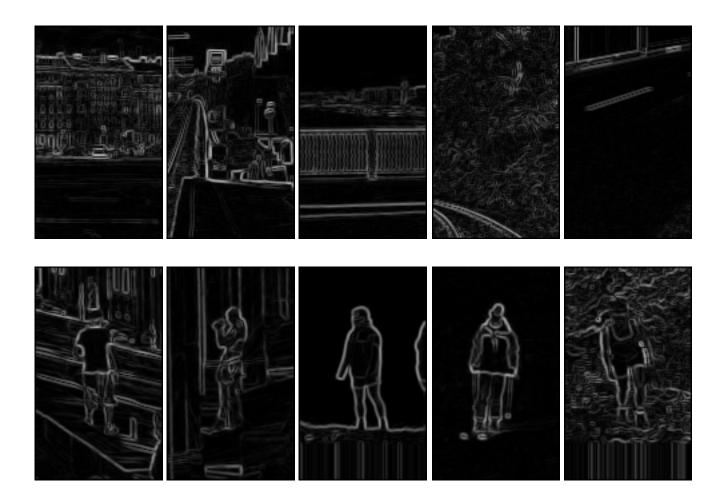
Accuracy: 80%

(E)

Additional comments: In order to find the optimal number of training epochs and training rate, I used a trial and error approach, eventually choosing those values to maximize my accuracy on classifying test images. By the end of training, all of the training images were generating output safely 100% within the correct classification, but this still did not guarantee a 100% accuracy rate when it came to then classifying test images.

(F)

Normalized Gradient Images



(G)

Source Code:

```
import math
import numpy as np
from PIL import Image
from random import seed
from random import random
import glob
#CREATE DIRECTORIES OF FILE PATHS TO ALL TRAINING AND TEST IMAGES training_negative_paths = [img for img in glob.glob("Human/Train_Negative/*.bmp")] training_positive_paths = [img for img in glob.glob("Human/Train_Positive/*.bmp")] test_positive_paths = [img for img in glob.glob("Human/Test_Positive/*.bmp")] test_negative_paths = [img for img in glob.glob("Human/Test_Neg/*.bmp")]
#HOG-
for j in range(96):
bw_image[i,j] = round(np.sum(rgb_to_gray*rgb_indexed[i,j]))
     return bw_image
#PRODUCE IMAGE GRADIENT MAGNITUDE AND GRADIENT ANGLE
def gradient(input_image_2):
    dim = input_image_2.shape
    #CREATE NEW, SEPARATE MATRICES FOR GX, GY, GRADIENT MAGNITUDE, and GRADIENT ANGLE
    gx_arr = np.zeros(dim, dtype=np.float)
    gy_arr = np.zeros(dim, dtype=np.float)
    gradient_magnitude = np.zeros(dim, dtype='float')
    gradient_angle = np.zeros(dim, dtype = 'float')
    # PREWITT OPERATOR USED TO CALCULATE GX AND GY
    prewitt_gx = np.array([[-1,0,1],
#PRODUCE IMAGE GRADIENT MAGNITUDE AND GRADIENT ANGLE
                                                                                                               [-1,0,1],
[-1,0,1]])
     prewitt_gy = np.array([[1,1,1],
                                                                                                               [0,0,0],
[-1,-1,-1]])
     \begin{array}{c} gy\_sum = 0 \\ gx\_sum += np.sum(img\_submatrix*prewitt\_gx) \\ gy\_sum += np.sum(img\_submatrix*prewitt\_gy) \\ gx\_arr[i,j] = abs(gx\_sum)/3 \\ gy\_arr[i,j] = abs(gy\_sum)/3 \\ gradient\_magnitude[i,j] = math.sqrt(gx\_arr[i,j]**2 + gy\_arr[i,j]**2) \\ gradient\_angle[i,j] = math.degrees(math.atan2(gy\_arr[i,j],gx\_arr[i,j])) \\ return (gradient\_magnitude, gradient\_angle) \end{array}
                                     gy\_sum = 0
#L2 NORMALIZATION PERFORMED ON EACH 36-DEGREE BLOCK VECTOR
def I2_normalize(block_input):
I2_norm = math.sqrt(np.sum(block_input**2))
if I2_norm == 0:
                  return block_input
      else:
                  normalized = block_input / I2_norm
     return normalized
#MAIN FUNCTION FOR PRODUCING HOG DESCRIPTOR
def hog_feature(image_path):
#OPEN IMAGE
     new_image = Image.open(image_path)
     #PREPROCESS IMAGE image_bw = make_grayscale(new_image) (gradient_magnitude, gradient_angle) = gradient(image_bw)
     height = gradient_magnitude.shape[0]
     width = gradient_magnitude.shape[1]
rows = height/8
columns = width/8
     #INITIZALIZE A ROWSXCOLUMNS MATRIX TO STORE 9-BIN HISTOGRAM FOR EACH CELL IN IMAGE
     cell_histogram = np.empty(shape=(rows,columns,9))
histogram_bin = np.zeros(9)
```

Project 2: Human Detector Neural Network

```
#CREATE CELL HISTOGRAM MATRIX
     for i_start in range(0,height,8):
                  for j_start in range(0,width,8):
                                   i_end = i_start + 8
j_end = j_start + 8
                                   row = i_start/8
column = j_start/8
                                   for i in range(i_start, i_end):
                                                     for j in range(j_start, j_end):
angle = gradient_angle[i,j]
                                                                      if angle < -10:
                                                                                        angle += 180
                                                                     weight_r = 1 - weight_l
                                                                       #POPULATE HISTOGRAM BINS USING WEIGHTED GRADIENT MAGNITUDES
                                                                       histogram_bin[bin_index[0]] += gradient_magnitude[i,j]*weight_l histogram_bin[bin_index[1]] += gradient_magnitude[i,j]*weight_r
                                   \begin{array}{c} \text{for x in range(9):} \\ \text{cell\_histogram[row,column,x] = histogram\_bin[x]} \end{array}
     #CREATE BLOCK HISTOGRAM MATRIX FROM CELLS hog_output = np.empty(shape=0) for i in range(rows-1):
                 for j in range(columns-1):
block = np.empty(shape=0)
                                   block = np.concatenate((block,cell_histogram[i,j]),axis=None)
block = np.concatenate((block,cell_histogram[i,j+1]),axis=None)
block = np.concatenate((block,cell_histogram[i+1,j]),axis=None)
block = np.concatenate((block,cell_histogram[i+1,j]),axis=None)
block_normal = 12_normalize(block)
hog_output = np.concatenate((hog_output,block_normal),axis=None)
     return hog_output
#NETWORK-----
#INITIALIZE NETWORK VARIABLES
input_size = 7524
hidden_size = 500
train_rate = 0.03
a_input = np.empty(0)
a_hidden = np.empty(hidden_size)
a_output = 0.0
                                                                                                         #WEIGHTS ARE INITIALIZED TO A RANDOM VALUE IN RANGE [0,1)
w_input = (np.random.rand(hidden_size,input_size))/hidden_size #WEIGHTS ARE INITIALIZED TO A RANDOM VALUE IN R. w_hidden = (np.random.rand(hidden_size))/hidden_size #WEIGHTS ARE INITIALIZED TO A RANDOM VALUE IN RANGE [0,1)
in_i = 0.0
in_j = np.empty(hidden_size)
delta_i = 0.0
delta_j = np.empty(hidden_size)
#ACTIVATON FUNCTIONS
```

```
def relu(x):
if x <= 0:
                 return 0
     else:
                return x
def relu_derivative(x):
    if x <= 0:</pre>
                return 0
     else:
                 return 1
def sigmoid(x):
return (1/(1+ math.e**(-x) ))
def sigmoid_derivative(x):
    return sigmoid(x)*(1-sigmoid(x))
 #TRAINING
 def forward_propogate(hog):
     global a_input
global a_hidden
global w_input
global w_hidden
global in_i
      ğlobal in_j
     a_input = hog[0]
     #FORWARD PROPOGATION
     #FORWARD PROPOGATION
for j in range(hidden_size):
    in_j[j] = np.sum(a_input*w_input[j])
    a_hidden[j] = relu(in_j[j])
in_i = np.sum(a_hidden*w_hidden)
output = sigmoid(in_i)
label = hog[1]
print('output: ', output, ' / label: ', label)
return (label, output)
 #SUBROUTINE CALLED BY BACK_PROPOGATE_ERROR
def update_weights():
global w hidden
     global w_input
global train_rate
global a_hidden
     global a_input
global delta_i
     global delta_j
     train_rate*a_hidden[j]*delta_i
     def back_propogate_error(error):
global delta_i
     global delta_j
global in_i
global in_j
      ğlobal w_hidden
      \begin{array}{l} \mbox{delta\_i} = \mbox{error * sigmoid\_derivative(in\_i)} \\ \mbox{for $j$ in range(hidden\_size):} \\ \mbox{delta\_i[j]} = \mbox{relu\_derivative(in\_j[j])*w\_hidden[j]*delta\_i} \\ \mbox{update\_weights()} \end{array} 
 #SUBROUTINE CALLED BY TRAIN-NETWORK -- RETURNS AVERAGE SQUARE ERROR OVER EACH EPOCH OF 20 IMAGES
 def average_error(error_cache):
     error_sum = 0
for i in range(20):
     error_sum += error_cache[i]**2/2
average = error_sum/20
     return average
 #MAIN DRIVING FUNCTION FOR TRAINING OUR NEURAL NETWORK
```

Project 2: Human Detector Neural Network