AuE 8200: Machine Perception and Intelligence

Homework 2

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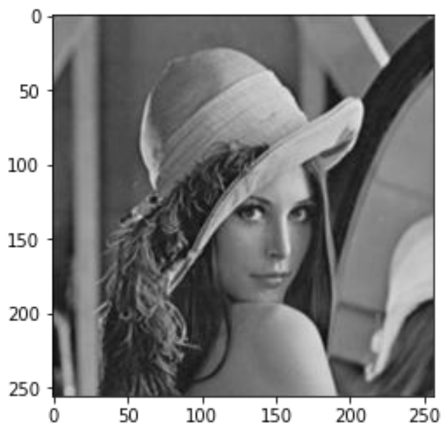
Question-1

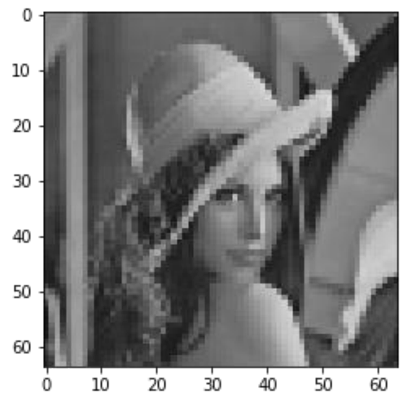
1-1) Convert the image from RGB to gray, using a standard RGB-intensity conversion approach like NTSC, and store the converted image "LennaGray.jpg" as an 8-bit gray image. (2 pts)

```
# Question 1-1)

### Convert the image from RGB to gray using a standard RGB-intensity conversion approach ###

LennaRGB = cv2.imread("Lenna.jpg")

"""Function to convert the RGB image to Gray scale color space"""

def RGB2GRAY(img):
    blue = 0.07*img[:,:,2]
    green = 0.72*img[:,:,1]
    red = 0.21*img[:,:,0]
    gray_img = red+blue+green
    return gray_img

LennaGray = RGB2GRAY(LennaRGB).astype(np.uint8)
cv2.imwrite("LennaGray.jpg", LennaGray)
display = plt.imshow(LennaGray, cmap='gray', vmin=0, vmax=255)
```



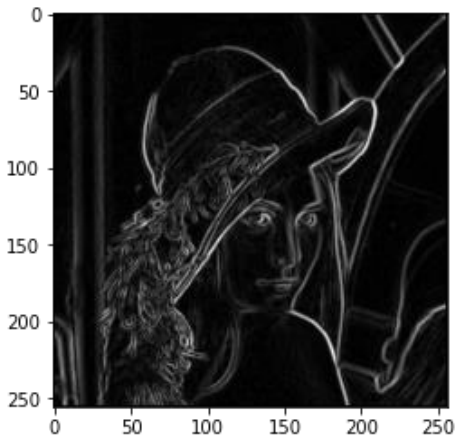
1-2) Down-sampling image "LennaGray.jpg" from size 256x256 to 64x64. (3 pts)
Perform the down-sampling and visualize your result.

```
# Question 1-2)

### Down-sampling from size 256x256 to 64x64 ###

img = cv2.imread("LennaGray.jpg")
pixels = []
r = int(256/64)

for i in range(0, img.shape[0]-3, r):
    for j in range(0, img.shape[1]-3, r):
        temp = img[i:i+4, j:j+4]
        pixels.append(np.mean(temp)) #taking mean from selected 4x4 pool to get one pixel value

pixels = np.array(pixels)
Resized_LennaGray = pixels.reshape(64, 64)

cv2.imwrite("Resized_LennaGray.jpg", Resized_LennaGray)
plt.imshow(Resized_LennaGray, cmap="gray", vmin=0, vmax=255)
plt.show()
```



1-3) Implement the convolution (using basic arithmetic operations only, rather than build-in conv()) of Sobel kernel on the “LennaGray.jpg” for edge detection, visualize and comment your detection result. (10 pts)

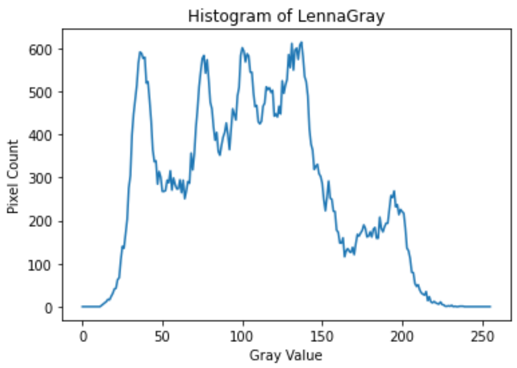
```
# Question 1-3)

### Implementing convolution of sobel kernel using airthmetic operation ###

sobel_filter_x = np.array([[-1, 0, 1], [-2, 0, 2], [-1, 0, 1]])
sobel_filter_y = np.array([[-1, -2, -1], [0, 0, 0], [1, 2, 1]])

"""Function to convert the Grayscale image to Sobel filtered image"""

def SobelFilter(Img):
    row, column = np.shape(Img)
    sobel_filtered_image = np.zeros(shape = (row, column))
    for i in range(row-2):
        for j in range(column-2):
            gx = np.sum(np.multiply(sobel_filter_x, Img[i:i + 3, j:j + 3]))  # x direction
            gy = np.sum(np.multiply(sobel_filter_y, Img[i:i + 3, j:j + 3]))  # y direction
            sobel_filtered_image[i + 1, j + 1] = np.sqrt(gx ** 2 + gy ** 2)  # estimating the "hypotenuse"
    plt.imshow(sobel_filtered_image, cmap=plt.get_cmap('gray'))

SobelFilter(LennaGray)
```



Question-2

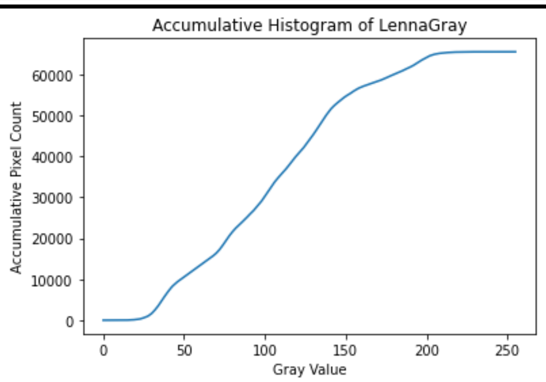
2 -1) Perform histogram analysis and visualize histogram distribution (2 pts);

```
# Question 2-1)

### Histogram analysis and visualization ###

"""Function to visualize the histogram of a grayscaled image"""

def hist(Img):
    row, column = np.shape(Img)
    value = [] #list to store gray values
    count = [] #list to store the count
    for h in range (0, 256):
        value.append(h)
        count1 = 0
        for i in range(row):
            for j in range(column):
                if Img[i,j] == h:
                    count1+=1
        count.append(count1)
    return (value, count)

value1, count2 = hist(LennaGray)
plt.xlabel('Gray Value')
plt.ylabel('Pixel Count')
plt.title('Histogram of LennaGray')
display = plt.plot(value1, count2)
```



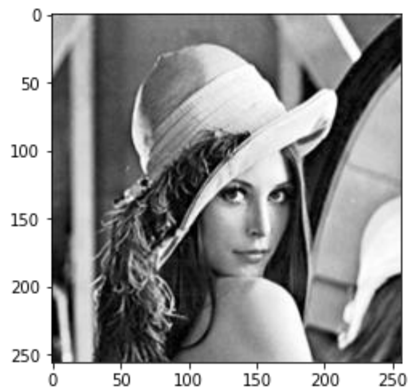
2-2) Calculate and visualize accumulative histogram distribution (3 pts);

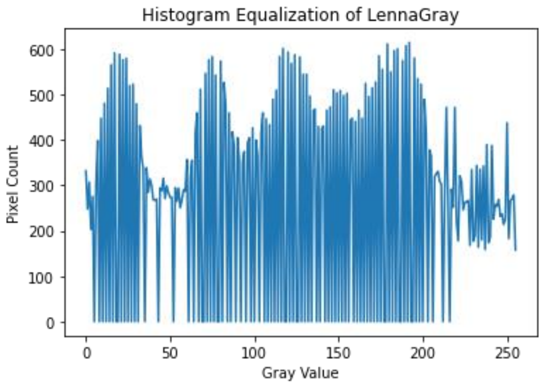
```
# Question 2-2)

### Accumulative Histogram analysis and visualization ###

accum = []
l = len(count2)
m = 0
for k in range(0, l):
    m+=count2[k]
    accum.append(m)
plt.xlabel('Gray Value')
plt.ylabel('Accumulative Pixel Count')
plt.title('Accumulative Histogram of LennaGray')
display = plt.plot(value1,accum)
```



2-3) Implement a function to perform histogram equalization for this image, visualize your histogram-equalized image and its histogram distribution. Comments the difference between the two images before/after histogram equalization. (10 pts);

```
# Question 2-3)

### Visualizing the histogram-equalized image and its histogram distribution. ###

"""Function to visualize the equalized image"""

def eq_hist(Img):
    eq_hist = np.zeros(256, dtype=int)
    Img_flat = Img.flatten()
    for i in range(0, len(eq_hist)):
        n = len(Img_flat)/256
        eq_hist[i] = max(0, (round(accum[i]/n) - 1))
    eq_img = np.zeros(Img.size, dtype=int)

    for j in range(0, Img.size):
        eq_img[j] = eq_hist[Img_flat[j]]
    eq_img = eq_img.reshape(256,256)
    return eq_img

"""Function to visualize the equalized histogram"""

def eq_hist_dist(Img):
    row, column = np.shape(Img)
    value = [] #list to store gray values
    count = [] #list to store the count
    for h in range (0, 256):
        value.append(h)
        count1 = 0
        for i in range(row):
            for j in range(column):
                if Img[i,j] == h:
                    count1+=1
        count.append(count1)
    return (value, count)

#Visualizing equalized histogram image
f = plt.figure()
eq_img = eq_hist(LennaGray)
display = plt.imshow(eq_img, cmap="gray", vmin=0, vmax=255)

#Visualizing equalized histogram distribution
f = plt.figure()
plt.xlabel('Gray Value')
plt.ylabel('Pixel Count')
plt.title('Histogram Equalization of LennaGray')
v, c = eq_hist_dist(eq_img)
display = plt.plot(v, c)
```

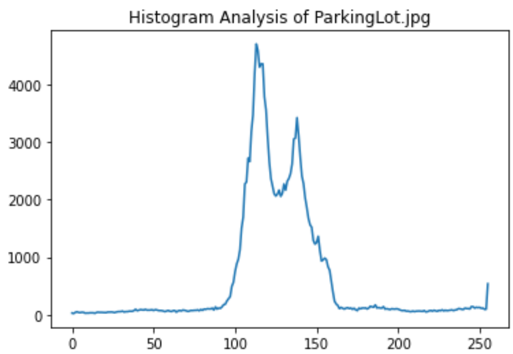


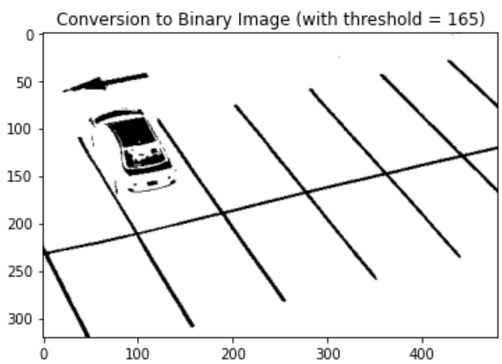


Question-3

3-1) Apply and visualize histogram analysis, then find a proper threshold to convert the image to a binary image. (2 pts)

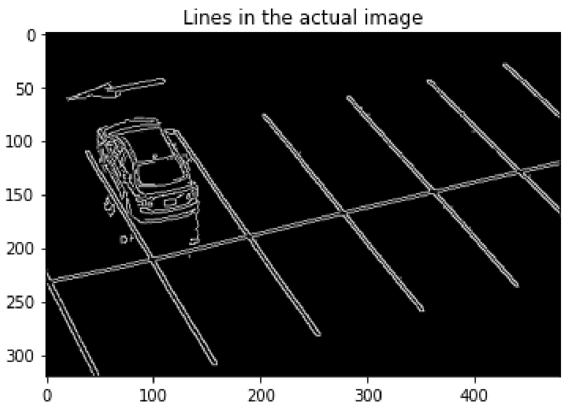
```
# Question 3-1)

image = cv2.imread('ParkingLot.jpg',0)

### Visualizing histogram analysis ###

histogram = cv2.calcHist([image],[0],None,[256],[0,256]) #estimating frequency of pixels in range 0-255
plt.plot(histogram)
plt.title('Histogram Analysis of ParkingLot.jpg')
display = plt.show()

### Converting image to binary image ###

ret, thresh1 = cv2.threshold(image, 165, 255, cv2.cv2.THRESH_BINARY_INV) #defining binary threshold as 165
cv2.imwrite("ParkingLotBinary.jpg", thresh1)
plt.title('Conversion to Binary Image (with threshold = 165)')
display = plt.imshow(thresh1, cmap=plt.get_cmap('gray'))
```

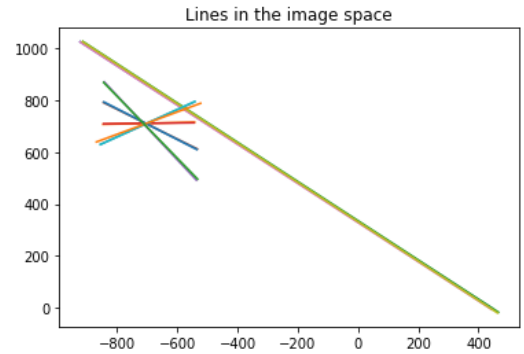


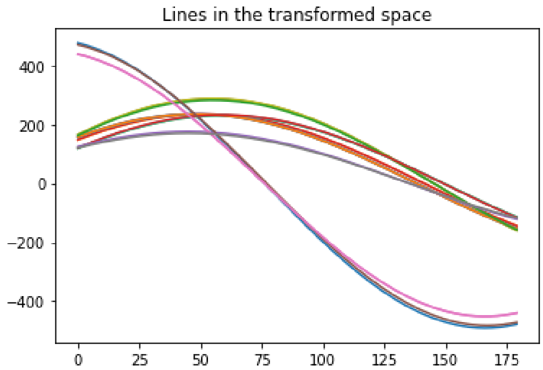


3-2) Apply Hough transformation or other line detection approach to detect multiple lines in the image (You select a threshold for the voting matrix). Visualize the lines in the image space and in the transformed space (like Polar space) respectively. (5 pts)

```
# Question 3-2)

### Visualizing Lines in the image ###

image = cv2.imread('ParkingLot.jpg')
grayscale = cv2.cvtColor(image,cv2.COLOR_BGR2GRAY)
edges = cv2.Canny(grayscale, 50, 150, apertureSize=3)
plt.figure()
plt.title('Lines in the actual image')
plt.imshow(edges, cmap = 'gray')

### Visualizing Lines in the image space ###

import math
image = cv2.imread('ParkingLot.jpg')
grayscale = cv2.cvtColor(image,cv2.COLOR_BGR2GRAY)
edges = cv2.Canny(grayscale, 50, 150, apertureSize=3)
plt.imshow(edges, cmap = 'gray')
lines = cv2.HoughLines(edges, 1, np.pi / 180, 150, None, 0, 0)

if lines is not None:
    plt.figure()
    plt.title('Lines in the image space')
    for i in range(0, len(lines)):
        rho = lines[i][0][0]
        theta = lines[i][0][1]
        a = math.cos(theta)
        b = math.sin(theta)
        x0 = a * rho
        y0 = b * rho
        pt1 = (int(x0 + 1000*(-b)), int(y0 + 1000*(a)))
        pt2 = (int(x0 - 1000*(-b)), int(y0 - 1000*(a)))
        cv2.line(image, pt1, pt2, (0,0,255), 3, cv2.LINE_AA)
        plt.plot(pt1,pt2)


### Visualizing the Lines in the transformed space ###

lines = cv2.HoughLinesP(edges, 1, np.pi / 180, 100, maxLineGap = 1000)
poles = []
theta = np.arange(0,np.pi,np.pi/180)
plt.figure()
plt.title('Lines in the transformed space')
for line in lines:
    x1,y1,x2,y2 = line[0]
    cv2.line(img, (x1, y1), (x2, y2), (0, 0, 255), 2)
    xa = x2 - x1
    ya = y2 - y1
    rho = xa * np.cos(theta) + ya*np.sin(theta)
    poles.append((y2-y1)/(x2-x1))
    plt.plot(rho)
stop = time.time()
```







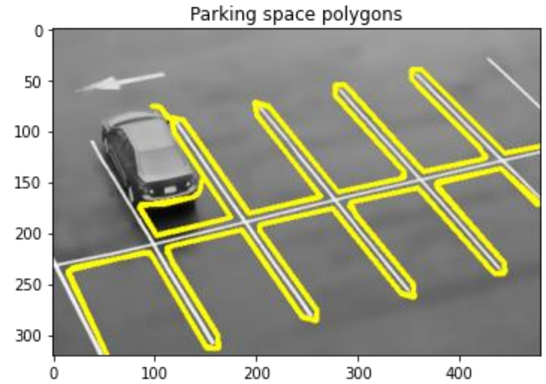
3-3) Comment on: will the two lines as two sides of a particular park space be parallel or not, explain why? (3 pts)

No, two sides of any particular parking spot are not parallel. This is mainly because when slopes of the lines were estimated it was not the same for any two nearby lines. Also, the approach used in the solution is based on approximation and this is why the lines estimated may not come to be parallel while they can be otherwise in reality.

3-4) Design and implement the approaches to find all parking space polygons with the four vertex points for each parking space. Describe your approaches and visualize all detected polygons with different colors overlaid on the original image. The TA will check your code. (20 pts)

```python
# Question 3-4)

### Parking space polygons ###

from scipy import misc
from scipy.ndimage import gaussian_filter
from scipy.signal import medfilt2d
import random

image = cv2.imread('ParkingLot.jpg')
image = cv2.bilateralFilter(image, 15, 80, 80,None)
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

threshold1=50
threshold2=250

testKernel = np.ones((5,5 ),np.float32)/49 #5x5 Kernel
gray = cv2.dilate(gray, testKernel, iterations=3)
gray = cv2.erode(gray, testKernel, iterations=1)

edged = cv2.Canny(gray, threshold1, threshold2)
kernel = np.ones((3,3), np.uint8)
contours, hierarchy = cv2.findContours(edged, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_NONE)
print("Number of Contours = " + str(len(contours)))
contoursFound = 0
totalContours = []

for contour in contours :
    area = cv2.contourArea(contour)
    print("area",area)

    # Shortlisting the regions based on there area.
    if area > 100:
        approx = cv2.approxPolyDP(contour,0.001 * cv2.arcLength(contour, True), True)
        M = cv2.moments(contour)
        cX = int(M["m10"] / M["m00"])
        cY = int(M["m01"] / M["m00"])

        cv2.drawContours(image, [approx], -1, (255, 255, 0), 3)

plt.title("Parking space polygons")
display = plt.imshow(image)
```

```
Number of Contours = 8
area 26.0
area 66.5
area 560.5
area 18.0
area 89.5
area 588.0
area 15.5
area 92.0
```



Question4: Survey

Animal Detection at Night in Automobiles

Importance of Measuring/Identifying Animals on Road

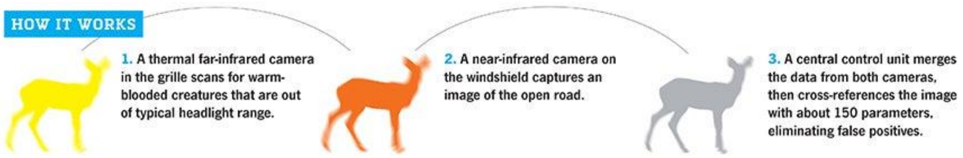
Vehicle-wildlife accidents are at a surge and result in environmental, economic, and personal losses. Many of these accidents cause human injuries, vehicle damage, and loss of wildlife.

To state it as a fact, over 2 million animal-related road accidents occur every year in the US, causing over 26,000 injuries per year to passengers in the vehicle. [1]

Challenges of Identifying Animals on Road

When a camera shoots at night, the picture is often too grainy to make out anything clearly. Hence, to capture obstacles, especially animals at night, it is crucial to alter the light and intensity of the camera.

Standard infrared night vision technologies are not much reliable on the road. For instance, some night vision cameras illuminate a scene with infrared and use reflection to make up an image, which is often not much accurate. This may work in identifying objects or animals, in this case at night, but if more than one car comes towards each other, all shooting infrared beams, then they'd blind each other cameras. To add on, infrared cameras do not pick colors which can be a factor aiding the identification of animals.



Source: https://www.popsci.com/technology/article/2013-08/infrared-car-system-spots-wildlife/

Furthermore, another challenge is that the algorithms and associated cameras would have to rapidly acclimate to changing conditions like car speed, light levels, surroundings.

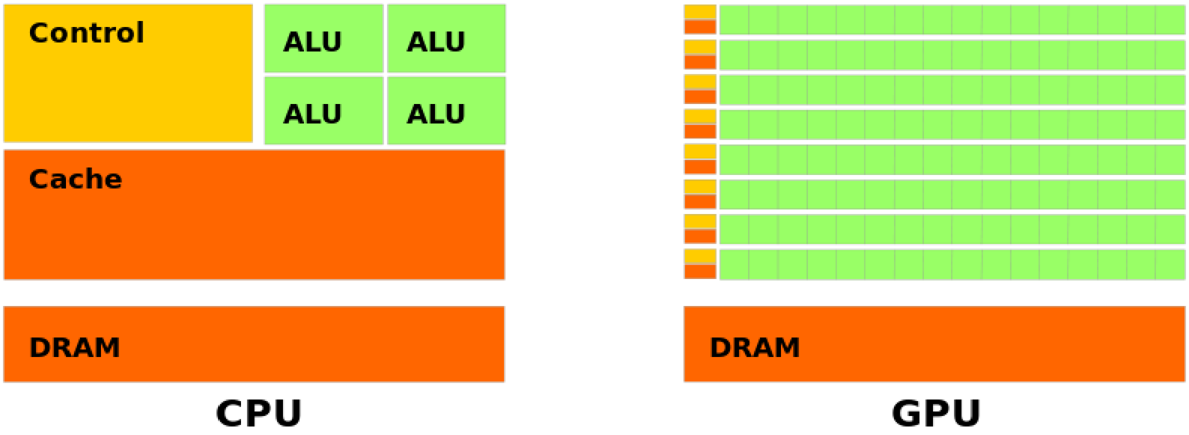
Existing Approaches of Identifying Animals on Road

The solution to this problem is inspired by animals themselves. Most nocturnal animals sum their visual inputs, adding together all the incoming light signals to perceive a much brighter image in two different ways. In other words, the brain of a nocturnal animal can combine light signals generated by several light receptors and sum up the signals coming over in many milliseconds. [2]

Achieving accuracy and precision from cameras at night by taking inspiration from nocturnal animals is not as easy as it may sound.

There is a plethora of numbers; for the vehicle computer to crunch and for the onboard cameras to do any good in the dark. Considering this, it is essential to make computers fast enough and write programs that would process images accurately and quickly on computer graphics cards to run calculations parallelly, thus reducing processing time.

Using GPUs' ability of faster parallel processing, more significant amounts of data can be processed in lesser time, thus allowing onboard cameras to identify objects like animals at night.



Source: *https://medium.com/codex/understanding-the-architecture-of-a-gpu-d5d2d2e8978b*

There are certain criteria for fast image processing –

Performance

Fast performance in image processing can be achieved in two ways: either by optimizing software code or by increasing hardware resources (like- number of processors). GPU easily outperforms CPU in the price to performance ratio.

Latency

The architecture of GPU allows parallel pixel processing leading to a reduction in latency (i.e., time taken to process one image). CPUs, on the other hand, have relatively modest latency.

Image processing quality

Several algorithms used for image processing algorithms differ in the quality of the result. Multilevel optimization is crucial for resource-intensive algorithms as it achieves essential performance benefits. After the multilevel optimization is implemented, applied algorithms can output the result in a reasonable time frame, comparable to the speed of fast but crude programs.[3]

Source: *https://www.flir.com/news-center/camera-cores--components/thermal-imaging-for-large-animal-detection-to-help-reduce-wildlife-vehicle-collisions/*

Existing Problems of These Existing Approaches

Employing GPUs for faster image processing to see animals at night has some limitations.

Firstly, GPUs have numerous cores running at lower clock speeds than CPUs typically employ. Secondly, since GPU does not have any virtual memory support, I/O support, privilege levels, no operating system can run on it. Lastly, GPUs are usually much more complex than CPUs because writing multithreaded programs is more arduous.

Furthermore, not to forget that identifying animals is much more complicated than identifying humans. To train the algorithm, a vast dataset of animals is needed. This is mainly because they can vary widely in shape and size and have profiles that change substantially when they move differently or turn. In comparison, humans more or less move in the same way and have the same shape.[4]

References

1. https://www.iii.org/fact-statistic/facts-statistics-deer-vehicle-collisions
2. https://www.scientificamerican.com/article/animal-cameras/
3. https://www.fastcompression.com/blog/gpu-vs-cpu-fast-image-processing.htm
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