Find my Photos!

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Data: 26/12/2023

Executive Summary:

This project is centered around the development and implementation of an advanced person detection system integrated with an image recognition algorithm. The primary objective is to accurately identify individuals within a given set of images and provide each person's photos in which he appears. The main outcome of it is to rearrange photos depending on the person, it will achieve speeding up searching for person photo which is a part of the big list of photos, and the results will be saving time. In conclusion, the person detection and image recognition system presented in this project significantly advances the capabilities of identifying individuals within images. Its high accuracy and efficient photo tracking functionality make it a versatile tool with wide-ranging applications.

Contents

Introduction

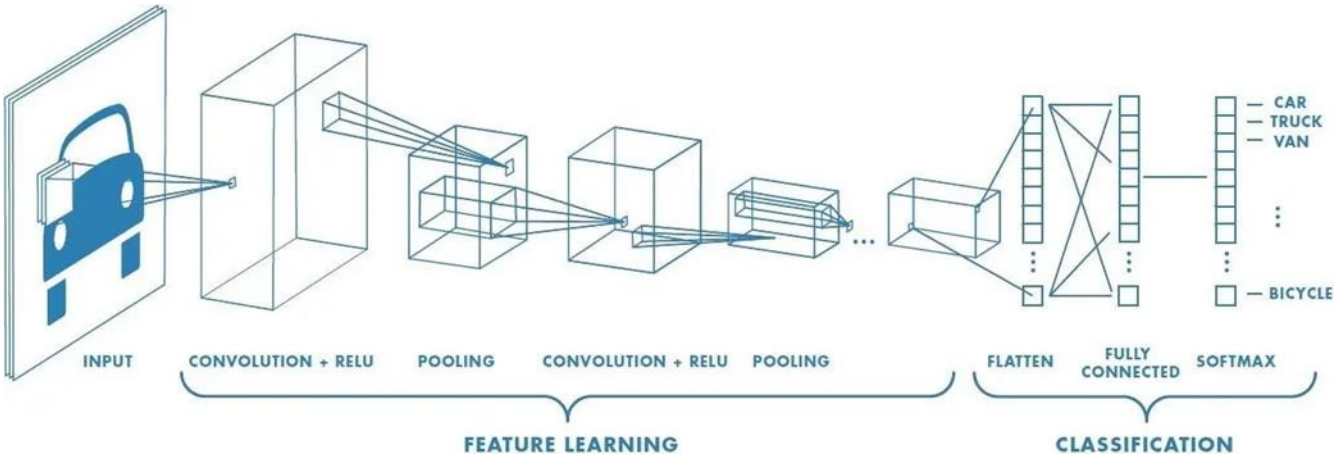
In the contemporary landscape of digital imagery, our project aims to tackle the challenge of efficiently navigating extensive photo collections. Situated at the convergence of image processing, face recognition, and user interface design, our application responds to the growing need for a seamless solution in identifying and retrieving individual portraits within curated photo repositories. As individuals and organizations grapple with the task of swiftly locating specific photos within a large list of photos, our project addresses this demand by streamlining the process. We outline clear objectives: implementing robust image processing techniques, incorporating advanced face detection and recognition algorithms, and creating an efficient search algorithm. The project scope encompasses the development of a user-friendly standalone application, processing photos in various formats, and adhering to ethical considerations regarding privacy. The subsequent sections of this report will delve into the methodology, technical intricacies, and considerations related to privacy, testing, and deployment, offering a comprehensive understanding of the application's development and functionality.

Literature Review

Facial detection and alignment play crucial roles in computer vision applications, including face recognition, human-computer interaction, and surveillance. This literature review explores two prominent approaches in the field: "Joint Face Detection and Alignment using Multitask Cascaded Convolutional Networks" by Zhang et al. and "Histograms of Oriented Gradients for Human Detection" by Dalal and Triggs. The objective is to understand the strengths and limitations of each method and discuss potential synergies for a combined approach. Multitask Cascaded Convolutional Networks for Face Detection and Alignment Zhang et al. proposed a novel approach that jointly addresses face detection and alignment using Multitask Cascaded Convolutional Networks (MTCNN). MTCNN consists of three cascaded stages: face proposal network (P-Net), refinement network (R-Net), and calibration network (O-Net). This architecture effectively handles faces at different scales, achieving state-of-the-art results in terms of accuracy and speed. The integration of tasks optimizes computation, making it suitable for real-time applications. MTCNN has very good points of strengths like High accuracy it demonstrates superior face detection and alignment accuracy, Multiscale processing which the cascaded architecture efficiently handles faces of varying sizes, Real-time applicability which is designed to allows for efficient processing, making it suitable for real-time applications. But it has one limitation. It depends on labeled data: MTCNN relies on large amounts of labeled data for training, which may be challenging to obtain for specific domains. The Histograms of Oriented Gradients (HOG) approach by Dalal and Triggs focuses on human detection but can be adapted for facial detection. HOG extracts gradient information from image regions and utilizes histograms to represent local object appearance and shape. It has strengths like Robust feature representation which it captures gradient information effectively, providing a robust representation of object appearance, Invariance to illumination changes: HOG is less affected by variations in lighting conditions, enhancing its generalization capabilities. But it has limitation like with color images which it operates on grayscale images, potentially limiting its performance in scenarios where color information is crucial, Sensitivity to scale changes which may face challenges in handling objects at different scales. Combining MTCNN and HOG leverages the strengths of both methods. MTCNN's multiscale processing and real-time applicability complement HOG's robust feature representation. Integrating these techniques could enhance the ability to get people photos per each person, especially when faced with challenges such as varying lighting conditions and scale changes.

Methodology

CNN information:

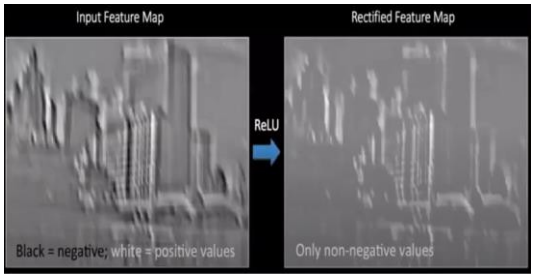


CNN stages consist of 3 stages, each stage consist of 3 (convolution, relu,polling(subsampling)):

1. **Convolutional:**

- A layer that consists of a set of "filters". Linear/matrix multiplications operations are performed by using a subset of the weights of a dense layer. Nearby inputs are connected to nearby outputs. The weights for the convolutions at each location are shared, but they go through an activation function at the output, which is usually a non-linear operation. (sigmoid).
- **Stride:** apply filter by each n pixel in left or down.
- **Types:**
  - ❖ valid: It means no padding, p = 0 so output will be n+2p - f+1 = n -f +1 [smaller]
    - EX: if you have a n by an image and convolve it with an f-by-f filter, then the dimension of the output will be (n-f+1) by (n-f+1).
    -And so, for the 6 by 6 image and the 3 by 3 filter on the left, the output image size would be a (6–3+1) by (6–3+1) which simplifies to a 4 by 4 output.
  - ❖ There are two problems when you convolve a filter to an image:
    - The shrinking output
    - Throwing away information from the edges of the image So Same come.
  - ❖ **same**: It means with padding so output will be n+2p – f+1 **[Same or bigger]**
  - ❖EX: if you have an n by an image and convolve it with an f-by-f filter, then the dimension of the output will be (n+2p – f+1) by (n+2p – f+1). And so, for the 6 by 6 image and the 3 by 3 filter on the left, the output image size would be a (6+2*1–3+1) by (6+2*1–3+1) which simplifies to a 6 by 6 output.
  - ❖ **full**: mix between them.
  - ❖ **Stride with padding**: output will be floor of [(n+2p-f)/S +1].

2. **ReLU (Rectified Linear Unit):** An activation functions commonly used in neural network.
   Definition: f(x)=max (0, x), where x is the input to the function.
   - if value 0 or smaller than 0 set it into 0
   - if bigger than 0 let it
   then purpose is to extract positive values only (features which we need, depending on conv filter which was applied)



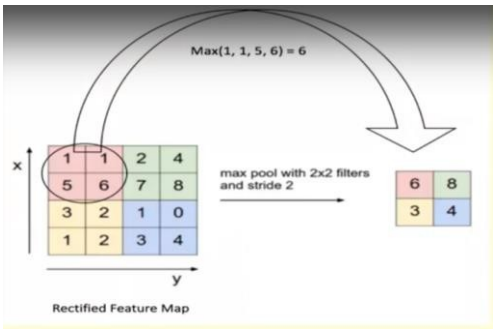
3. **PReLU** (Parametric Rectified Linear Unit): is an extension of ReLU
   It introduces a learnable parameter to the activation function.

   - **Definition**: f(x)=max (0, x) +a·min(0,x), where a is a learnable **parameter**.

   # **Pooling**: Replace each block in the input with a single output

   can be **max**: get the max value from batch.
   can be **sum** SIGMA (pixel * kernel element)/ n of pixels.

   Purpose:
   1- Force model to learn from important values only and disallow noise and garbage from moving.
   2- Decreasing complexity



   # **Flatten**: convert last layer 3D output into a 1D vector

   # **Dense** (fully connected layer): A linear operation, describes how the neurons are connected to the next layer of neurons, generally followed by a non-linear activation function (sigmoid)
   subcooling: values will go to half using 2 X 2 filter and take the biggest of the 4 pixels.

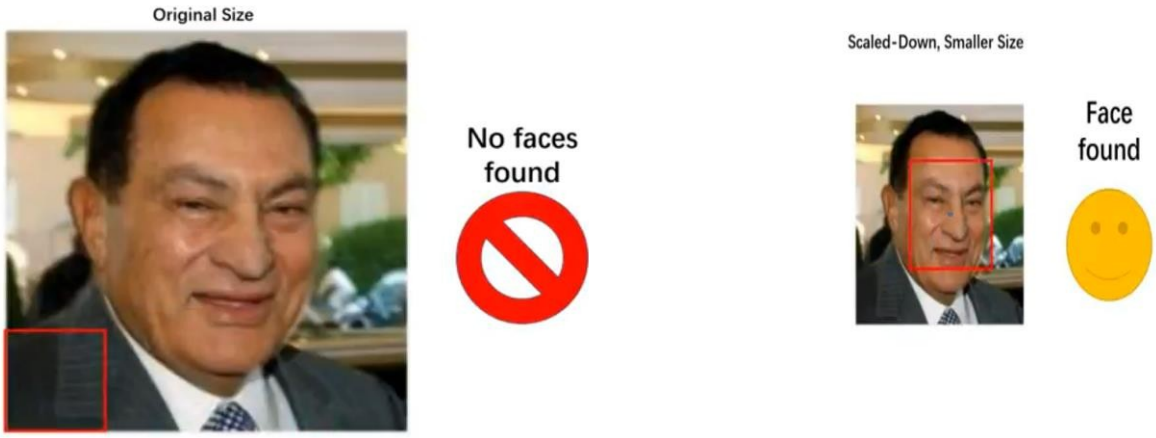
   # **Dropout**: telling to use n% from neurns to prevent overfitting

   # **Softmax** : activation function is applied to scores to convert them into probabilities [0 to 1].

   # **Output layer**: Produces the final predictions.

MTCNN Multi-task Cascaded Convolutional Networks:

Classification:



Design Process:

- **Algorithm Design:**

Before starting with algorithm, we should resize input image into two different scales to build. an image pyramids. There is a question which should be answered why pyramids? The answer is so easy to be able to make different copies of the same image in different sizes to search for different sized faces within the image. This makes the downside which we must recalculate all indexes related to the stride therefore we have to multiply the index by 2 to get the correct coordinate.

The proposed CNNs consist of 3 stages:

Most convolution layer uses stride of 2 why? Having a stride of 2 helps reduce computation operations to quarter therefore complexity without significantly sacrificing accuracy.

First stage is called Proposal Network (P-Net):

The weights and biases of P-Net have been trained so that it outputs a relatively accurate bounding box.

1- All coordinates are being normalized from (0,0) top left corner to (1,1) bottom right corner.
The weights and biases of P-Net have been trained so that it outputs a relatively accurate bounding box.
2 - It calculates confidence [0 to 1] to be face by the help of convolution layer filters for each generated boxs [many are not accurate]
3- It sorts them from highest confidence to the lowest confidence.
4- It picks out boxes with higher confidence
5- It standardizes the coordinate system which means converting all the coordinate systems to that of the actual “un-scaled” image.

We face 2 issues:

1- a lot of bounding boxes left.

2- 2- a lot of them overlap.

So, we found a solution. It is easy to use **Non-Maximum Suppression (NMS).**

1- We check overlapping using something is called (IoU) we will talk about it later.

2- check 2 overlapping boxes confidence

3- Remove box which lowers confidence.

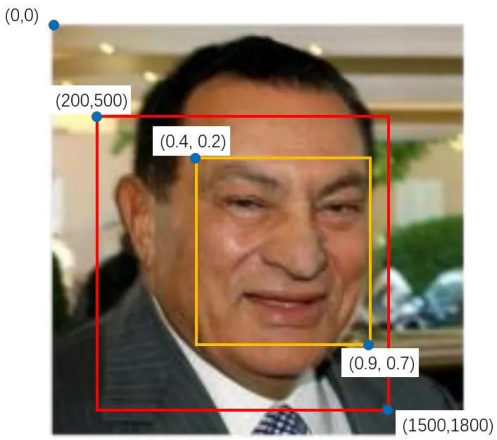
Therefore, it gets rid of redundant bounding boxes, allowing us to narrow our search down to one accurate box per face.

Kernel Coordinates	Bounding box: x1	Bounding box: y1	Bounding box: x2	Bounding box: y2	Confidence
(0,5)	0.50	0.25	0.80	0.58	0.98
(0,6)	0.45	0.17	0.75	0.49	0.96
(0,7)	0.52	0.08	0.73	0.41	0.94
(1,4)	0.42	0.34	0.67	0.66	0.92
(1,8)	0.40	0.01	0.66	0.32	0.96
(3,5)	0.32	0.22	0.49	0.59	0.88
(3,6)	0.25	0.20	0.52	0.53	0.91
(6,6)	0.01	0.18	0.25	0.50	0.89
(6,8)	0.02	0.00	0.22	0.33	0.90

There is good question why we don't we just choose the box with the highest confidence and delete everything else? There might be more than one face in other images. If so, we would end up deleting all the bounding boxes for the other faces.

Now lets take box coordinates from normalized scaled and converting it to coordinates in actual scale , lets take example :

In image,24 x 24 kernel is represented by the red box,
We can calculate the width and height of the kernel:
500–200 = 300, 800–500 = 300
The width and height we get here are the width and height of the kernel when scaled back to its original size.
300 * 0.4 = 120, 300 * 0.2 = 60
300 * 0.9 = 270, 300 * 0.7 = 210

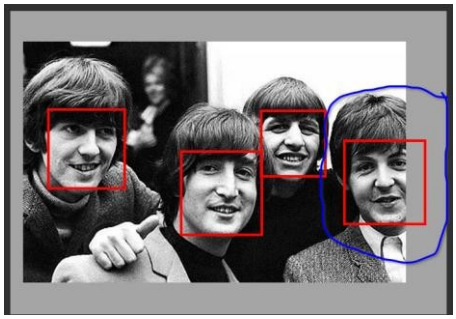


Finally, actual cord:
- (200+120, 500+60) => (320,560)
- (200+270, 500+210) => (470,710).

To achieve square bounding boxes, we adjust their shapes by extending the shorter sides. If the width is less than the height, we expand horizontally; conversely, if the height is less than the width, we expand vertically. This reshaping ensures uniformity in the bounding box dimensions.

Finally, bounding boxes were saved and passed on to second stage.

Second stage is called Refine Network (R-Net):
Sometimes, an image may contain only a part of a face peeking in from the side of the frame. In that case, the network may return a bounding box.



For every bounding box:
1 - We create an array of the same size
2 - Copy the pixel values (the image in the bounding box) to the new array.
3 - Fill in everything else with a 0. [process of filling arrays with 0s is called **padding**.]
4 - We resize them to 24 x 24 pixels
5 - Normalize them to values between -1 and 1:
  - Currently, the pixel values are between 0 to 255 (RGB values).
  - By subtracting each pixel value by half of 255 (127.5) and dividing it by 127.5,
  - we can keep their values between -1 and 1.

We can feed them into R-Net and gather its output.

R-Net's output is like that of P-Net: It includes:

- The coordinates of the new, more accurate bounding boxes.
- Well as the confidence level of each of these bounding boxes.
- we eliminate the boxes with lower confidence
- apply NMS on every box to further eliminate redundant boxes.

Since the coordinates of these new bounding boxes are based on the P-Net bounding boxes, we need to convert them to the standard coordinates.

After standardizing the coordinates, we reshape the bounding boxes to a square to be passed on to O-Net.

Third stage is called Output Network (O-Net):
We have to first pad any boxes that are out-of-bounds. After we resize the boxes to 48 x 48 pixels, we can pass in the bounding boxes into O-Net

Once again, we get rid of the boxes with lower confidence levels and standardize both the bounding box coordinates and the facial landmark coordinates. Finally, we ran them through the last NMS. At this point, there should only be one bounding box for every face in the image.

O-Net provides 3 outputs:
- the coordinates of the bounding box (out [0])
- the coordinates of the 5 facial landmarks (out [1])
- the confidence level of each box (out [2]).

• Coding Practices:
- python: 3.11
- libraries:

- **cv2: is a computer vision and machine learning software library.**
- **NumPy: is a powerful numerical computing library for Python.**
- **pkg_resources :** It provides runtime facilities for finding, introspecting, and managing Python packages and their resources.
- **TensorFlow:** TensorFlow is an open-source machine learning framework developed by the Google Brain team.
- **keras :** is an open-source high-level neural networks API written in Python
- **tensorflow.keras.layers :** contains various pre-built layers for building neural network models,such as dense layers, convolutional layers, and recurrent layers.
- **tensorflow.keras.models :** provides functionalities for defining and training neural network models.

Data Acquisition:

In the learning process we need different types of images (face, non-face and incompletely aligned face) for training each CNN such as :

1- FDDB (“Face Detection Dataset and Benchmark”) : contains a set of 2,845 images contains annotations for 5171 faces.

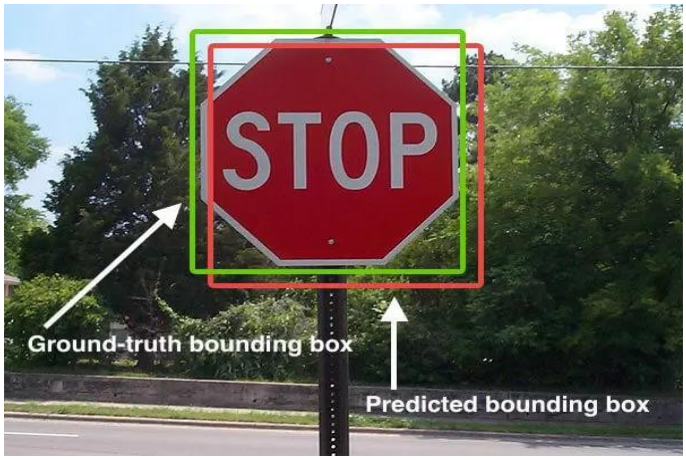
2- WIDER FACE has 32,203 images which has 32,203 images where

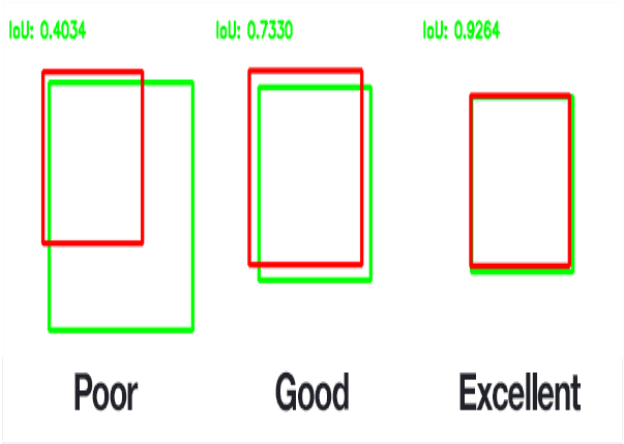
A - 50% for testing according to the difficulty of images spitted into 3 groups
B - 40% for training
C - 10% for validation

3- AFLW contains the facial landmarks annotations for 24,386 faces

4- CelebA (“Celebrities Attributes”) is a large-scale face attributes dataset was created at the Chinese Academy of Sciences.

Four types of data annotation in our training process but before that we should speak about Intersection over Union (IoU).





It is an evaluation metric’s performance of object detection by comparing the ground truth bounding box to the preddicted bounding box and it is being computed as dividing the area of overlap between the bounding boxes by the area of union.

Let’s return to types:

A) Negatives: Regions that the Intersection-over-Union (IoU) ratio less than 0.3 to any ground-truth
faces

B) Positives: IoU above 0.65 to a ground truth face.

C) Part faces: IoU between 0.4 and 0.65 to a ground truth face.

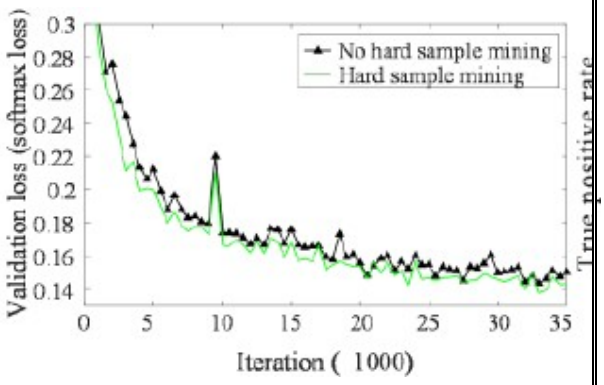
D) Landmark faces: faces labeled 5 landmarks’ positions.

1) P-Net:
- We randomly crop several patches from WIDER FACE to collect positives, negatives and part face.
- Then we crop faces from CelebA as landmark faces

2) R-Net:
- Detect face from wider face to collect posituves , negatives and partface while landmark faces are detected from CelebA

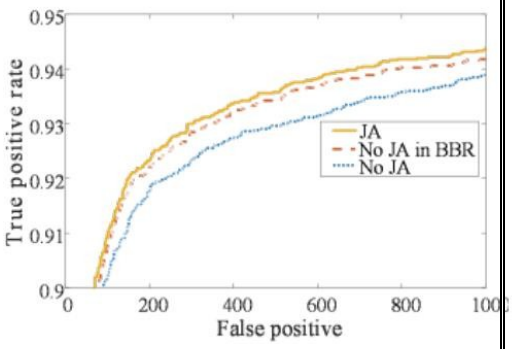
3) O-Net:
Similar to R-Net to collect data but we use the first two stages of our framework to detect faces.

Before speaking about the effectiveness of online hard sample mining. Let's know some about it. It is a technique used in machine learning in the context of training deep neural networks, to improve the learning process by focusing on challenging. The term "online" indicates that this process occurs dynamically during the training procedure rather than being applied as a separate pre-processing step.



The effectiveness of online hard sample mining
we train two O-Nets (with and without online hard sample mining) and compare their loss curves.
And We are using same training parameters including the network initialization
1- O-Nets was trained to classify the face.
2- Fix learning rate.
shows the loss curves from two different training ways. It is very clear that the hard sample mining is beneficial to performance improvement.

The effectiveness of joint detection and alignment
We can find that joint landmarks localization task learning is important for both face classification and bounding box regression tasks via
1- check the performances of two different O-Nets (joint facial landmarks regression task / do not join it) on FDDB (with the same First 2 layer).
2- compare the performance of bounding box regression in these two O-Nets.



Testing Methods:
The accuracy of model was 95.4%

TABLE I

COMPARISON OF SPEED AND VALIDATION ACCURACY OF OUR CNNS AND PREVIOUS CNNS [19]

Group	CNN	300 Times Forward	Accuracy
Group1	12-Net [19]	0.038s	94.4%
Group1	P-Net	0.031s	94.6%
Group2	24-Net [19]	0.738s	95.1%
Group2	R-Net	0.458s	95.4%
Group3	48-Net [19]	3.577s	93.2%
Group3	O-Net	1.347s	95.4%

HOG (Histogram of Oriented Gradients):

Design Process:

• **Algorithm Design:**

Logic:

HOG is a feature descriptor used for object detection in images. It works by capturing the distribution of gradient orientations in localized regions of an image. The basic idea is to represent an object based on the gradients of intensity in different directions, which helps capture the object's shape and edges.

Theory:

1- Gradient Computation:

Compute the gradient magnitudes and orientations of the image using first-order derivatives or Sobel masks. This step helps in detecting changes in light intensity, emphasizing edges and object boundaries.

2- Spatial/Orientation Binning:

Divide the image into cells and further divide each cell into grids. For each grid, create histograms of gradient orientations based on the gradient magnitudes within that grid. This process helps capture local information about the image.

3- Block Normalization:

Normalize the histograms within blocks of cells. This step is crucial for maintaining gradient values, ensuring that variations in illuminance do not affect the performance significantly. Common normalization methods include L2-Hys, L2-norm, L1-sqrt, and L1-norm.

4- Get the HOG Feature Vector:

Construct a feature vector by concatenating the normalized histograms from all blocks. The feature vector represents the distribution of gradient orientations in the entire image.

Steps to Perform HOG:

1- Gamma/Color Normalization (Optional):

Adjust color intensities using gamma correction. This step is optional and might involve experimenting with different color spaces, but it has a minor impact on the overall HOG descriptor.

2- Gradient Computation:

Compute gradients using first-order derivatives or Sobel masks. Choose the appropriate method for color or grayscale images.

3- Spatial/Orientation Binning (Dividing the image into cells):

Divide the image into cells and further into grids. Calculate histograms of gradient orientations within each grid.

4- Block Normalization:

Normalize histograms within blocks of cells to account for variations in illuminance.

5- Get the HOG Feature Vector:

Concatenate normalized histograms to form a feature vector representing the entire image.

Advantages

HOG is effective for object detection, especially in scenarios like pedestrian detection and medical image analysis.

It is computationally efficient for detecting small-scaled objects without requiring a powerful GPU.

Coding Practices:

Programming Language: *Python*

Libraries/Tools:

the Histogram of Oriented Gradients (HOG) algorithm is commonly implemented using various image processing libraries. Some of the popular libraries and tools that provide functions for HOG feature extraction include:

OpenCV*:*

OpenCV (Open Source Computer Vision Library) is a widely-used computer vision library that includes functions for HOG feature extraction. The cv2.HOGDescriptor class in OpenCV allows you to compute HOG descriptors for images.

dlib*:*

dlib is a C++ toolkit with Python bindings that includes machine learning and computer vision algorithms. The dlib.get_frontal_face_detector() function can be combined with HOG for face detection.

Data Acquisition:

The Histogram of Oriented Gradients (HOG) algorithm itself doesn't have a specific dataset associated with it. Instead, the choice of dataset depends on the specific task you are trying to solve using HOG, such as object detection, human detection, or face recognition.

Datasets:

MIT Pedestrian Database:

A collection of images containing pedestrians in city scenes.

Comprises 509 training images and 200 test images, with front or back views and limited pose variations

Commonly used for evaluating pedestrian detection algorithms.

INRIA Dataset:

A more challenging dataset with 1805 images of humans cropped from personal photos.

Features individuals in various orientations against diverse backgrounds, including crowds.

Includes bystanders from image backgrounds, introducing pose and background variability.

Training

Positive Training Examples:

Selected 1239 positive training examples from the INRIA dataset and their left-right reflections (2478 images in total).

Negative Training Examples:

Utilized a fixed set of 12,180 patches sampled randomly from person-free training photos as initial negative examples.

Detector Training:

Trained a preliminary detector using positive and negative examples.

Conducted an exhaustive search for false positives (hard examples) in 1218 negative training photos.

Retrained the detector using the augmented set (initial negative set + hard examples) to produce the final detector.

Retraining Process:

Significantly improved detector performance, especially at low false positive rates.

Additional rounds of retraining were considered but deemed not necessary.

Project Methodology:

Design Process:

- **Algorithm Design:**

1- Read path of images from folder
2- Read image and save it into object and make list of images
3- Use MTCNN to get faces boxes cord with threshold [0.8, 0.9, 0.9]
min confidence for each layer
4- Convert mtcnn box format into face_recognition box format.:
face_recognition : top, right, bottom, left
MTCNN: left top Rightp(width) bottomP(height)
5- Use face_recognition to calculate encoding using hog with
[num_jitters=100] to rescale and zoom and etc. to extract more details
6- Make Person List and ConnectiontoList
7- Create Persons from First image
8- Create Connection between first image and each person
9- Check images from second images to last image:
- if person exist in Person List [using encoding difference]: add connection then break
- if person exist in Person List: Create Person, add connection then break
10- start check PersonList
- check each person's connections.

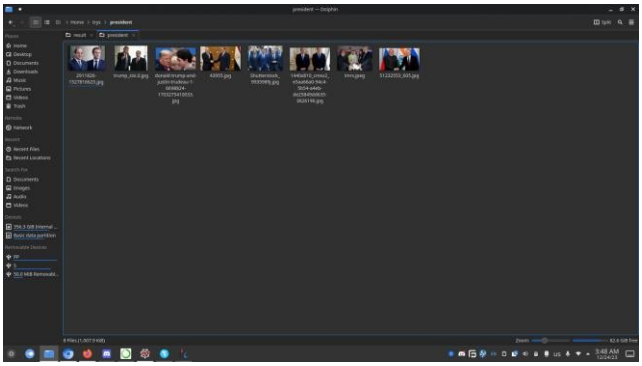
- **Coding Practices:**

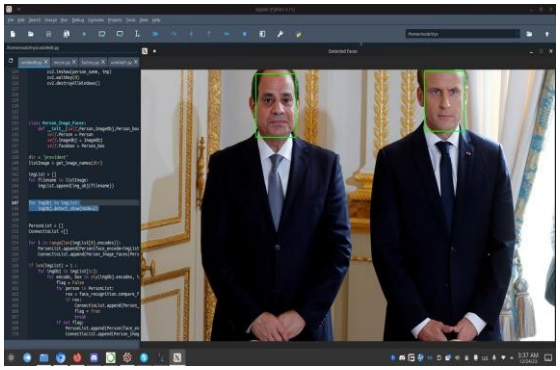
python: 3.11
libraries:
- cv2: is a computer vision and machine learning software library.
- copy: create copy of image
- Faker: Use random names
- tkinter: standard GUI (Graphical User Interface) toolkit for the Tk GUI toolkit.
- os: Access OS stuff like files
- mtcnn: for face classification
- face_recognition: for using hog algorithm to calculate encode for each person
- dlib : has face_recognition dependences
- cuda drivers: For using GPU in calculation

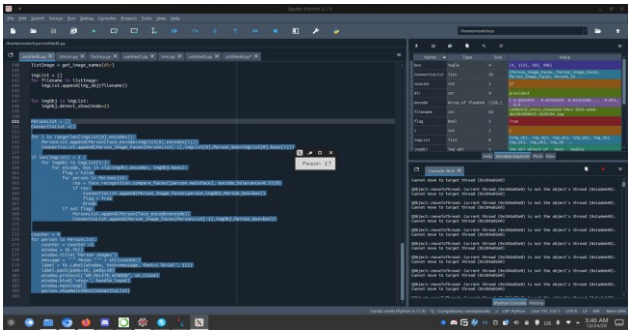
Data Acquisition: We don't use any data to train, because mtcnn is already trained, just push pictures.

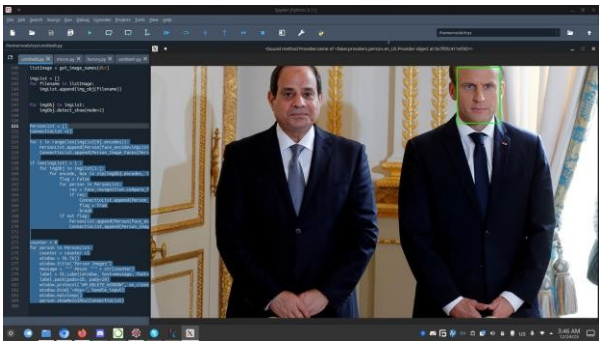
Testing Methods:

- Successfully Read input image from path **[Success]**
- Classify faces **[Success]**
- Recognize each person faces in images **[Success]**





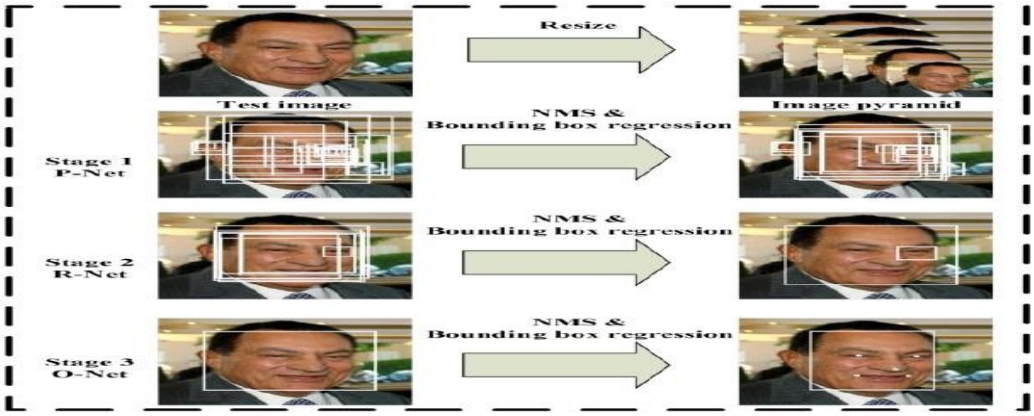




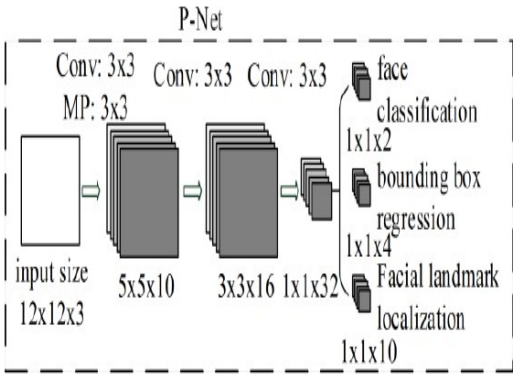
Technical Details:

MTCNN

• **System Architecture:**



P-Net:



Input Layer: 12x12 kernels

1- Convolution layer 10 kernel each of them is 3x3 using valid
PreLU layer
max pooling with using same

2- Convolution layer 16 kernel each of them is 3x3 using valid
PreLU

3 Convolution layer 32 kernel each of them is 3x3 using valid.
PreLU

The third layer activation is separate to convolution layers, and a softmax layer after one of those convolution layers (softmax assigns decimal probabilities to every result, and the probabilities add up to

Probabilities: (face in the area or there **isn't** a face).

4- Convolution 4–1 outputs the probability of a face being in each bounding box, and convolution 4–2 outputs the coordinates of the bounding boxes.

There is no Dense Layer here [Fully connected Layer]

R-Net:

Input Layer : 24x24 kernels

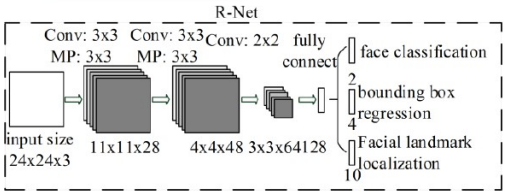
1- Convolution layer 28 kernel each them is 3x3 using valid
PreLU layer
max pooling with using same

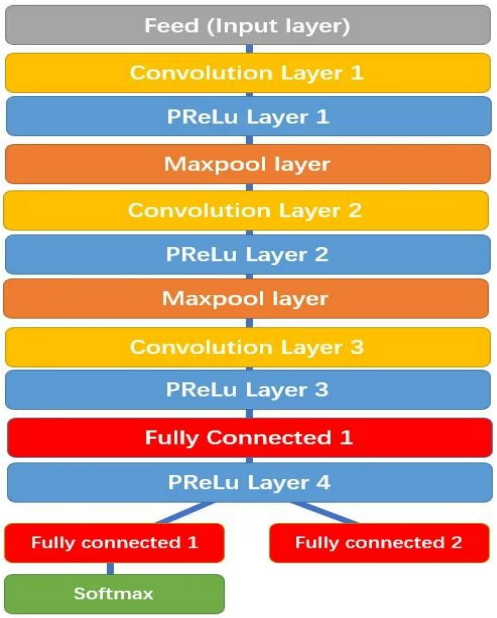
2- Convolution layer 48 kernel each them is 3x3 using valid
PreLU
max pooling with using valid

3- Convolution layer 64 kernel each them is 3x3 using valid
PreLU
Flatten
fully connected layer with 128 dim
PreLU

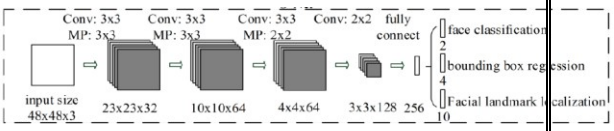
4- output 1 layer fully connected layer with 2 neurons and softmax for face classification
output 2 layer fully connected layer with 4 neurons for bounding
box regression

Similarly, R-Net splits into two layers in the end, giving out two outputs: the coordinates of the new bounding boxes and the machine's confidence in each bounding box





O-Net:



input: reshape into (48, 48, 3)

1- Convolution layer 32 kernel each of them is 3x3 using valid
PreLU layer
max pooling with using same

2- Convolution layer 64 kernel each of them is 3x3 using valid
PreLU
max pooling with using valid.

3- Convolution layer 64 kernel each of them is 3x3 using valid
PreLU
max pooling with using same

4- Convolution layer 128 kernel each them is 3x3 using valid
PreLU
fully connected layer with 256 neurons
PreLU

5- out1 : fully connected layer with 2 neurons and softmax for face classification
out2 : fully connected layer with 4 neurons for bounding box regression
out3 : fully connected layer with 10 neurons for facial landmark localization 2 for 5 (locations of the eyes, nose, mouth)

•Algorithm Explanation:

Training

We use three tasks to train CNN detectors: face/non-face classification, bounding box regression, and facial landmark localization.

1) Face classification: The **learning objective** is formulated as a two-class classification problem.

For each sample , we use the **cross-entropy loss**:

$$L_i^{det} = -(y_i^{det} \log(p_i) + (1 - y_i^{det})(1 - \log(p_i)))$$

where is the probability produced by the network that indicates a sample being a face. The notation

$\hat{y}_i^{det} \in \{0,1\}$ denotes label of ground-truth.

2) Bounding box regression: For each indow, we predict the offset between it and the nearest

ground truth .The learning objective is formulated as a regression problem, and we employ the Euclidean loss for each sample :

$$L_i^{box} = \left\| \hat{y}_i^{box} - y_i^{box} \right\|_2^2$$

where $\hat{y}_i^{box}$ regression target obtained from the network and y_i^{box} is the ground-truth coordinate. There are four coordinates, including left top, height and width, and thus $y_i^{box} \in R^4$

3) Facial landmark localization: Similar to the bounding box regression task, facial landmark detection is formulated as a regression problem and we minimize the Euclidean loss:

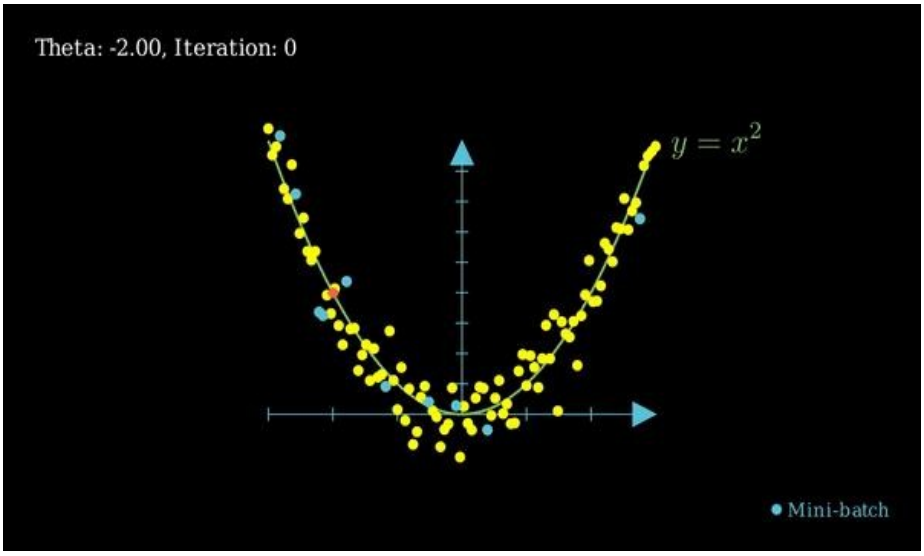
$$L_i^{landmark} = \left\| \hat{y}_i^{landmark} - y_i^{landmark} \right\|_2^2$$

where $\hat{y}_i^{landmark}$ is the facial landmark's coordinate obtained from the network and $y_i^{landmark}$ is the ground-truth coordinate. There are five facial landmarks, including left eye, right eye,nose, left mouth corner, and right mouth corner, and thus $y_i^{landmark} \in R^{10}$

4) Multi-source training:
Since we employ different tasks in each CNNs, there are different types of training images in the learning process, such as face, non-face and partially alignedface. In this case, some of the loss functions (Eq. (1)-(3))) are not used. For example, for the sample of background region, we only compute L_i^{det} , and the other two losses are set as 0. This can be implemented directly with a sample type indicator. Then the overall learning target can be formulated as:

$$\min \sum_{i=1}^{N} \sum_{j \in \{det, box, landmark\}} \alpha_j \beta_i^j L_i^j$$

where is the number of training samples. denotes on the task importance. We use $\alpha_{det=1}$, $\alpha_{box=0.5}$, $\alpha_{landmark=0.5}$ in P-Net and R-Net, ($\alpha_{det=1}$, $\alpha_{box=0.5}$, $\alpha_{landmark=1}$)in O-Net for more accurate facial landmarks localization . β_i^j is the sample type indicator. In this case, it is natural to employ stochastic gradient descent to train the CNNs.



• **Code Implementation:**

Welcome to Network Factory where mtcnn is being built.

P-net:

```
def build_pnet(self, input_shape=None):
    if input_shape is None:
        input_shape = (None, None, 3)

    p_inp = Input(input_shape)

    p_layer = Conv2D(10, kernel_size=(3, 3), strides=(1, 1), padding="valid")(p_inp)
    p_layer = PReLU(shared_axes=[1, 2])(p_layer)
    p_layer = MaxPooling2D(pool_size=(2, 2), strides=(2, 2), padding="same")(p_layer)

    p_layer = Conv2D(16, kernel_size=(3, 3), strides=(1, 1), padding="valid")(p_layer)
    p_layer = PReLU(shared_axes=[1, 2])(p_layer)

    p_layer = Conv2D(32, kernel_size=(3, 3), strides=(1, 1), padding="valid")(p_layer)
    p_layer = PReLU(shared_axes=[1, 2])(p_layer)

    p_layer_out1 = Conv2D(2, kernel_size=(1, 1), strides=(1, 1))(p_layer)
    p_layer_out1 = Softmax(axis=3)(p_layer_out1)

    p_layer_out2 = Conv2D(4, kernel_size=(1, 1), strides=(1, 1))(p_layer)

    p_net = Model(p_inp, [p_layer_out2, p_layer_out1])

    return p_net
```

R-Net:

```
def build_rnet(self, input_shape=None):
    if input_shape is None:
        input_shape = (24, 24, 3)

    r_inp = Input(input_shape)

    r_layer = Conv2D(28, kernel_size=(3, 3), strides=(1, 1), padding="valid")(r_inp)
    r_layer = PReLU(shared_axes=[1, 2])(r_layer)
    r_layer = MaxPooling2D(pool_size=(3, 3), strides=(2, 2), padding="same")(r_layer)

    r_layer = Conv2D(48, kernel_size=(3, 3), strides=(1, 1), padding="valid")(r_layer)
    r_layer = PReLU(shared_axes=[1, 2])(r_layer)
    r_layer = MaxPooling2D(pool_size=(3, 3), strides=(2, 2), padding="valid")(r_layer)

    r_layer = Conv2D(64, kernel_size=(2, 2), strides=(1, 1), padding="valid")(r_layer)
    r_layer = PReLU(shared_axes=[1, 2])(r_layer)
    r_layer = Flatten()(r_layer)
    r_layer = Dense(128)(r_layer)
    r_layer = PReLU()(r_layer)

    r_layer_out1 = Dense(2)(r_layer)
    r_layer_out1 = Softmax(axis=1)(r_layer_out1)

    r_layer_out2 = Dense(4)(r_layer)

    r_net = Model(r_inp, [r_layer_out2, r_layer_out1])

    return r_net
```

O-Net:

```
def build_onet(self, input_shape=None):
    if input_shape is None:
        input_shape = (48, 48, 3)

    o_inp = Input(input_shape)
    o_layer = Conv2D(32, kernel_size=(3, 3), strides=(1, 1), padding="valid")(o_inp)
    o_layer = PReLU(shared_axes=[1, 2])(o_layer)
    o_layer = MaxPooling2D(pool_size=(3, 3), strides=(2, 2), padding="same")(o_layer)

    o_layer = Conv2D(64, kernel_size=(3, 3), strides=(1, 1), padding="valid")(o_layer)
    o_layer = PReLU(shared_axes=[1, 2])(o_layer)
    o_layer = MaxPooling2D(pool_size=(3, 3), strides=(2, 2), padding="valid")(o_layer)

    o_layer = Conv2D(64, kernel_size=(3, 3), strides=(1, 1), padding="valid")(o_layer)
    o_layer = PReLU(shared_axes=[1, 2])(o_layer)
    o_layer = MaxPooling2D(pool_size=(2, 2), strides=(2, 2), padding="same")(o_layer)

    o_layer = Conv2D(128, kernel_size=(2, 2), strides=(1, 1), padding="valid")(o_layer)
    o_layer = PReLU(shared_axes=[1, 2])(o_layer)

    o_layer = Flatten()(o_layer)
    o_layer = Dense(256)(o_layer)
    o_layer = PReLU()(o_layer)

    o_layer_out1 = Dense(2)(o_layer)
    o_layer_out1 = Softmax(axis=1)(o_layer_out1)
    o_layer_out2 = Dense(4)(o_layer)
    o_layer_out3 = Dense(10)(o_layer)

    o_net = Model(o_inp, [o_layer_out2, o_layer_out3, o_layer_out1])
    return o_net
```

The Trigger to build it is in MTCNN CLASS:

```
class MTCNN(object):
    """
    Allows to perform MTCNN Detection ->
        a) Detection of faces (with the confidence probability)
        b) Detection of keypoints (left eye, right eye, nose, mouth_left, mouth_right)
    """

    def __init__(self, weights_file: str = None, min_face_size: int = 20, steps_threshold: list = None,
                 scale_factor: float = 0.709):
        """
        Initializes the MTCNN.
        :param weights_file: file uri with the weights of the P, R and O networks from MTCNN. By default it will load
        the ones bundled with the package.
        :param min_face_size: minimum size of the face to detect
        :param steps_threshold: step's thresholds values
        :param scale_factor: scale factor
        """
        if steps_threshold is None:
            steps_threshold = [0.6, 0.7, 0.7]

        if weights_file is None:
            weights_file = pkg_resources.resource_stream('mtcnn', 'data/mtcnn_weights.npy')

        self._min_face_size = min_face_size
        self._steps_threshold = steps_threshold
        self._scale_factor = scale_factor

        self._pnet, self._rnet, self._onet = NetworkFactory().build_P_R_O_nets_from_file(weights_file)
```

```python
def build_P_R_O_nets_from_file(self, weights_file):
    weights = np.load(weights_file, allow_pickle=True).tolist()

    p_net = self.build_pnet()
    r_net = self.build_rnet()
    o_net = self.build_onet()

    p_net.set_weights(weights['pnet'])
    r_net.set_weights(weights['rnet'])
    o_net.set_weights(weights['onet'])

    return p_net, r_net, o_net
```

HOG(Histogram of Oriented Gradients):

The feature descriptor defines an image by capturing color intensity and outlining edges using first-order directive kernels. It calculates gradient magnitude, determines orientation, and creates a histogram with bins storing gradient magnitudes based on orientation angles.

Steps to perform HOG:

- Gamma/Color Normalization (Optional)
- Gradient Computation
- Spatial/Orientation Binning (Dividing the image into cells).
- Block Normalization.
- Get the HOG Feature Vector.

Step 1: Gamma/Color Normalization (Optional):

Gamma normalization adjusts illuminance or color intensities using a power-law transformation. Experimentation with color spaces (e.g., RGB, LAB) shows minimal impact on HOG descriptors, especially with block normalization. This step is optional; you can skip it or test effects during free time. Gamma correction is demonstrated below.

```
S = C.R^(gamma)
To encode gamma,
gamma= 1/gamma
To decode gamma,
gamma= gamma

C = color intensity
R = (Image_input)/C
```

Step 2: Gradient Computation:

Compute image gradients using a simple 1-D [-1,0,1] mask for optimal results in detecting changes in light intensity.

Forward Difference: $$f'(x) = \frac{f(x+h) - f(x)}{h}$$

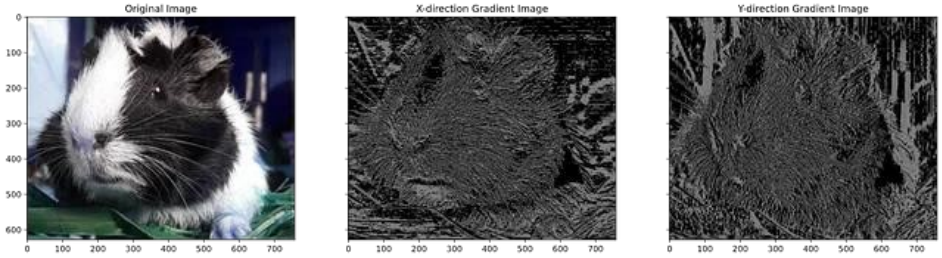
Backward Difference: $$f'(x) = \frac{f(x) - f(x-h)}{h}$$

Central Difference: $$f'(x) = \frac{f(x+h) - f(x-h)}{2h}$$

Magnitude : $$||\nabla f|| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

Direction : $$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$$

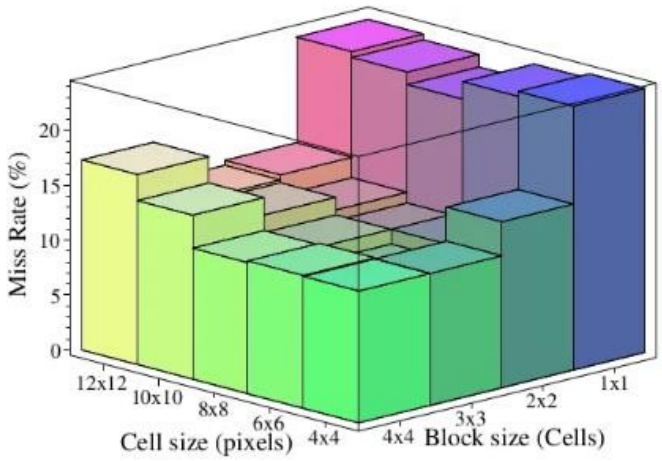
The horizontal gradient detects horizontal edges, and the vertical gradient detects upright position edges. In a colored image, gradient values are sharper than in grayscale. Square root transformation is applied to both horizontal and vertical gradient magnitudes for histogram creation. Simultaneously, orientation magnitudes are obtained using the arctangent of Y and X values.



Step 3: Spatial/Orientation Binning (Dividing the image into cells)

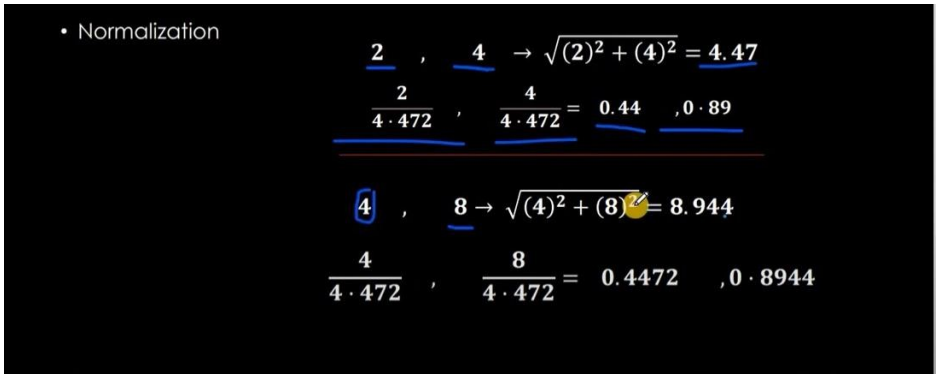
Scan the image in 63 x 63 blocks with a 2 x 2 grid of 8 x 8 pixels in each, resulting in 8 x 8 gradients and orientations. Each cell contains 128 values. Customize grid cells, blocks, and orientation bins (default is 8 x 8 cells with 4 grids per block). Increasing orientation bins up to 9 improves performance. Choose 'signed' (0–180) or 'unsigned' (0–360) degree values for histograms. For human detection, use 3 x 3 cell blocks with 6 x 6-pixel cells for optimal results.

.



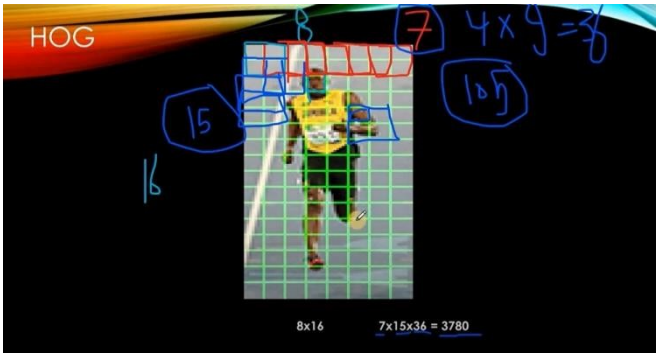
Step 4: Block Normalization:

To address variations in gradient values due to illuminance differences, normalize cells using block normalization. Apply this to each 2 x 2 grid, choosing from four schemes. L2-Hys, L2-norm, and L1-sqrt perform equally well, while L1-norm reduces performance by 5%.



Step 5: Get the HOG Feature Vector:

After block normalization, obtain the feature vector. With 9 orientation bins, each 8x8 grid generates 9 feature vectors. In a 4-grid block, you get 36 feature vectors, resulting in a 36 x 1 vector for a 16 x 16 block. For a 512 x 512 image with 63 x 63 blocks, the final feature vector is 142,884-dimensional. This is smaller than the 786,432 features in a colored image without HOG descriptors, making the HOG feature vector construction and visualization a multistep process.



Pre

```
import cv2
import copy
from faker import Faker
import tkinter as tk
import os
from mtcnn import MTCNN
import face_recognition
```

```
def on_close(event):
    window.destroy()
```

```
def handle_input(event):
    # Check if the input is '0' and close the window if true
    if event.char == '0':
        window.destroy()
```

class person:

```
class Person:
    def __init__(self,face_encode,name=None):
        # result = value_if_true if condition else value_if_false
        self.name = Faker().name if name is None else name
        self.mainface = face_encode



    def showMeInIMGs(self,connections):
        print("Person  : "+str(self.name)+"\n")
        for connection in  connections:
            if connection.Person == self:
                connection.ImageObj.selectface(connection.facebox,str(self.name))
```

class image:

```
def detect_faces(self):
    detector = MTCNN(steps_threshold=[0.8, 0.9, 0.9])
    return detector.detect_faces(self.image)
```

```python
def detect_show(self,mode):
    # mode 1 = MTCNN
    # mode 2 = face_recognition
    tmp = self.getimage_copy()
    tmp = cv2.cvtColor(tmp, cv2.COLOR_BGR2RGB)
    if mode == 1:
        for left, top, rightp, bottomP in  self.boxs_mtcnn:
            cv2.rectangle(tmp, (left, top), (left+rightp, top+bottomP), (0, 255, 0), 2)
    elif mode == 2:
        for top, right, bottom, left in self.boxs:
          cv2.rectangle(tmp, (left, top), (right, bottom), (0, 255, 0), 2)
    cv2.imshow('Detected Faces', tmp)
    cv2.waitKey(0)
    cv2.destroyAllWindows()
```

```python
def getimage_copy(self):
    return copy.deepcopy(self.image)
```

```python
def convertMTCNNT2FRT(self,boxes):
    myboxs = []
    for left, top, rightp, bottomP in boxes:
        # face_recognition : top, right, bottom, left
        # MTCNN : left top Rightp(width) bottomP(height)
        right = left+rightp
        bottom = top+bottomP
        myboxs.append((top,right,bottom,left))
    return myboxs
```

```python
def getfaceinpic(self,box,index=0):
    tmp = self.getimage_copy()
    tmp = cv2.cvtColor(tmp, cv2.COLOR_BGR2RGB)
    top, right, bottom, left = box
    cv2.rectangle(tmp, (left, top), (right, bottom), (0, 255, 0), 2)
    cv2.imshow('Detected Face '+str(index), tmp)
    cv2.waitKey(0)
    cv2.destroyAllWindows()
```

```
self.image_path = image_path
self.image = face_recognition.load_image_file(dir+'/'+image_path)
# FOR PERSENTATION
#self.image=cv2.resize(self.image, (800,600))
self.faces = self.detect_faces()
self.boxs_mtcnn = [tuple(d['box']) for d in self.faces]
self.boxs = self.convertMTCNNT2FRT(self.boxs_mtcnn)
print("I: I am going to calculate Encoding , it will take time")
self.encodes  = face_recognition.face_encodings(self.image,self.boxs,num_jitters=100)
if self.encodes:
    print("I: DOne PRO")
```

```
    def selectface(self,face_boxs,person_name):
        tmp = self.getimage_copy()
        tmp = cv2.cvtColor(tmp, cv2.COLOR_BGR2RGB)
        top, right, bottom, left = face_boxs
        cv2.rectangle(tmp, (left, top), (right, bottom), (0, 255, 0), 2)
        cv2.imshow(person_name, tmp)
        cv2.waitKey(0)
        cv2.destroyAllWindows()
```

class connection:

```
class Person_Image_Faces:
    def __init__(self,Person,ImageObj,Person_box):
        self.Person = Person
        self.ImageObj = ImageObj
        self.facebox = Person_box
```

Main:

```
dir = "president"
listImage = get_image_names(dir)
```

```
imgList = []
for filename in listImage:
    imgList.append(img_obj(filename))
```

```
for imgObj in imgList:
    imgObj.detect_show(mode=2)
```

```
PersonList = []
ConnectioList =[]
```

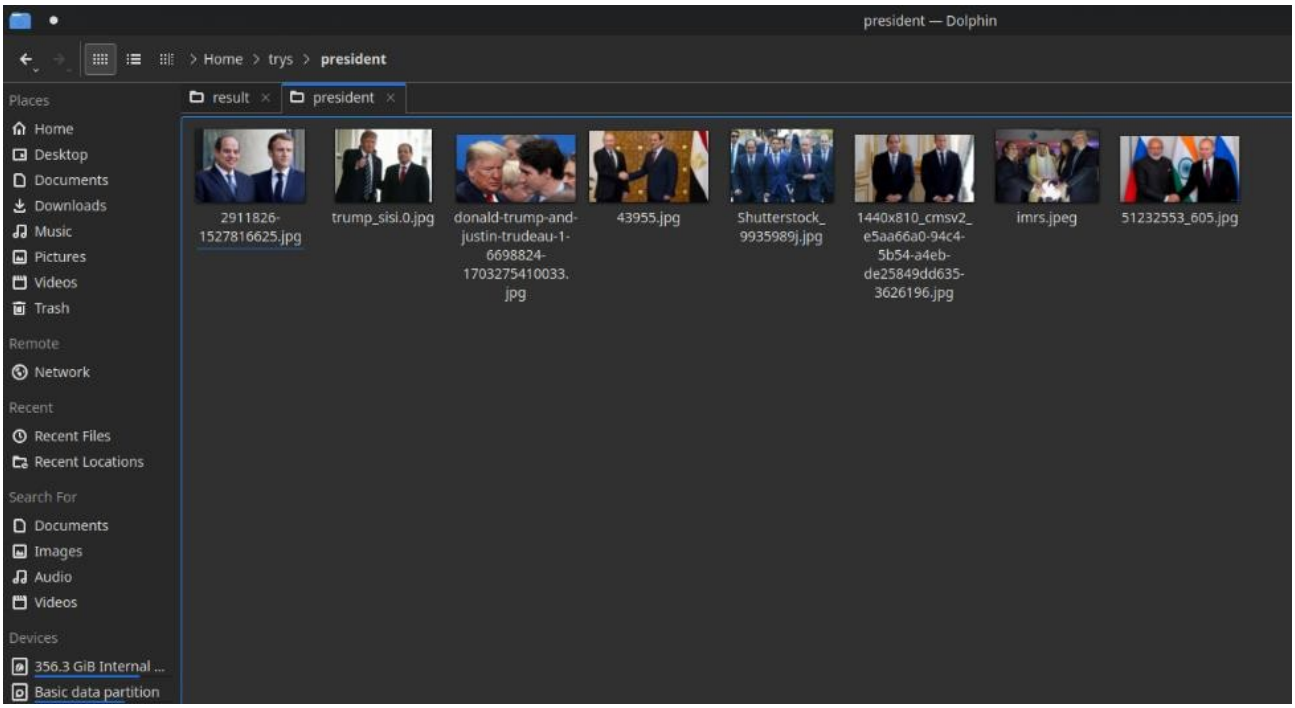
```
    for i in range(len(imgList[0].encodes)):
        PersonList.append(Person(face_encode=imgList[0].encodes[i]))
        ConnectioList.append(Person_Image_Faces(PersonList[-1],imgList[0],Person_box=imgList[0].boxs[i]))
```

```
if len(imgList) > 1 :
    for imgObj in imgList[1:]:
        for encode, box in zip(imgObj.encodes, imgObj.boxs):
            flag = False
            for person in PersonList:
                res = face_recognition.compare_faces([person.mainface], encode,tolerance=0.5)[0]
                if res:
                    ConnectioList.append(Person_Image_Faces(person,imgObj,Person_box=box))
                    flag = True
                    break
            if not flag:
                PersonList.append(Person(face_encode=encode))
                ConnectioList.append(Person_Image_Faces(PersonList[-1],imgObj,Person_box=box))
```

```
counter = 0
for person in PersonList:
    counter = counter +1
    window = tk.Tk()
    window.title("Person Images")
    message = """ Peson """ + str(counter)
    label = tk.Label(window, text=message, font=("Arial", 12))
    label.pack(padx=10, pady=10)
    window.protocol("WM_DELETE_WINDOW", on_close)
    window.bind('<Key>', handle_input)
    window.mainloop()
    person.showMeInIMGs(ConnectioList)
```

Result

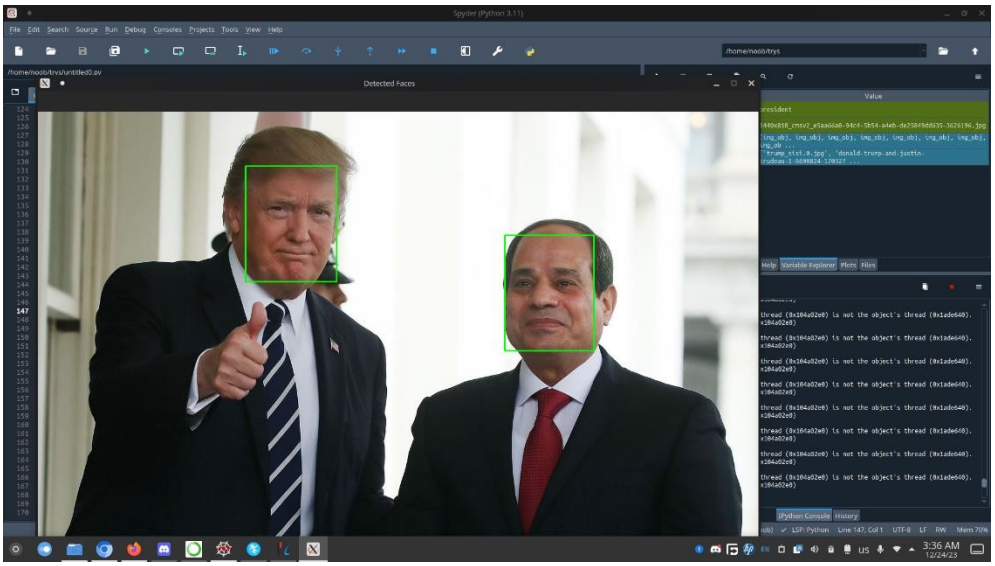
Input images:

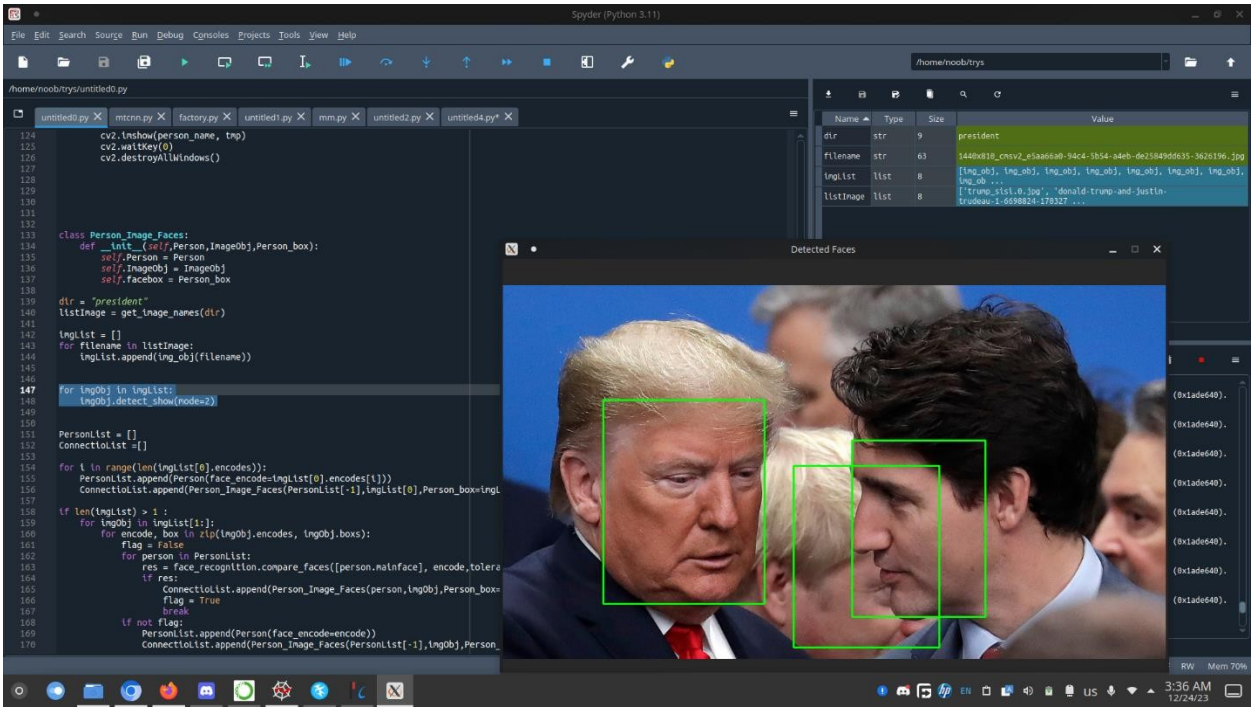


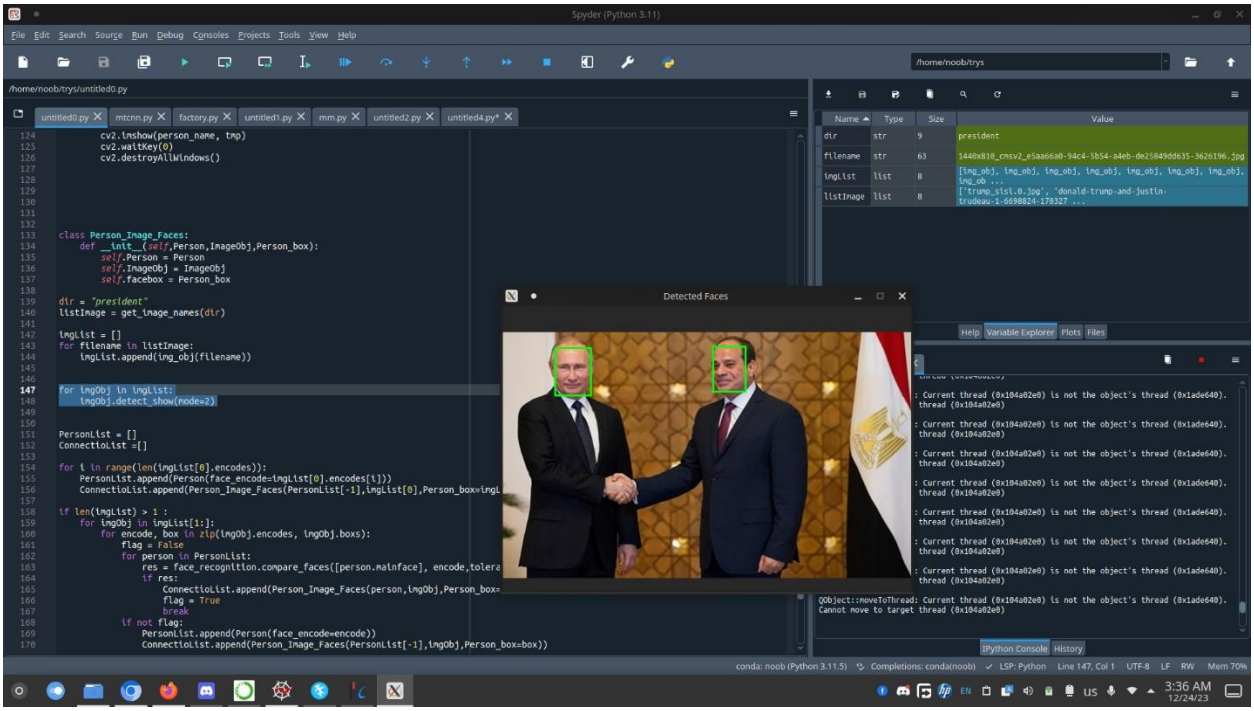
- Images have many people for each image.

Classification-Result:

- Check the image and predict image has a person or not if predicted person draws a square for his face using a box coordinate generated by O-NET based on confidence.




Spyder (Python 3.11)
File Edit Search Source Run Debug Consoles Projects Tools View Help
/home/noob/trys
/home/noob/trys/untitled0.py
untitled0.py
mtcnn.py
factory.py
untitled1.py
mm.py
untitled2.py
untitled4.py*
cv2.imshow(person_name, tmp)
cv2.waitKey(0)
cv2.destroyAllWindows()
class Person_Image_Faces:
def __init__(self,Person,ImageObj,Person_box):
self.Person = Person
self.ImageObj = ImageObj
self.facebox = Person_box
dir = "president"
listImage = get_image_names(dir)
imgList = []
for filename in listImage:
imgList.append(img_obj(filename))
for imgObj in imgList:
imgObj.detect_show(node=2)
PersonList = []
ConnectioList =[]
for i in range(len(imgList[0].encodes)):
PersonList.append(Person(face_encode=imgList[0].encodes[i]))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgList[0],Person_box=imgL
if len(imgList) > 1 :
for imgObj in imgList[1:]:
for encode, box in zip(imgObj.encodes, imgObj.boxs):
flag = False
for person in PersonList:
res = face_recognition.compare_faces([person.mainface], encode,tolera
if res:
ConnectioList.append(Person_Image_Faces(person,imgObj,Person_box=
flag = True
break
if not flag:
PersonList.append(Person(face_encode=encode))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgObj,Person_
Name Type Size Value
dir str 9 president
filename str 63 1440x810_cnsv2_e5aa66a0-94c4-5b54-a4eb-de25849dd635-3626196.jpg
imgList list 8 [img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_ob ...
listImage list 8 ['trump_sisi.0.jpg', 'donald-trump-and-justin-trudeau-1-6698824-178327 ...
Detected Faces
(0x1ade640).
RW Mem 70%
3:36 AM
12/24/23


Spyder (Python 3.11)
File Edit Search Source Run Debug Consoles Projects Tools View Help
/home/noob/trys
/home/noob/trys/untitled0.py
untitled0.py
mtcnn.py
factory.py
untitled1.py
mm.py
untitled2.py
untitled4.py*
cv2.imshow(person_name, tmp)
cv2.waitKey(0)
cv2.destroyAllWindows()
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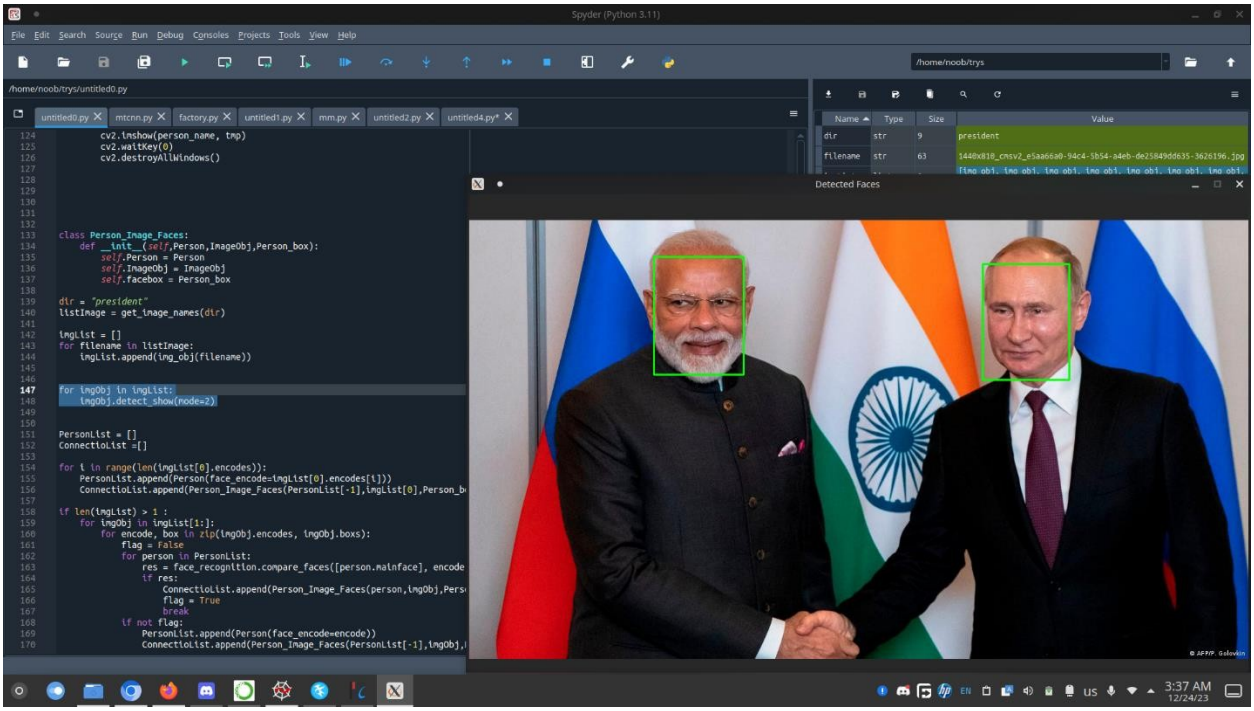
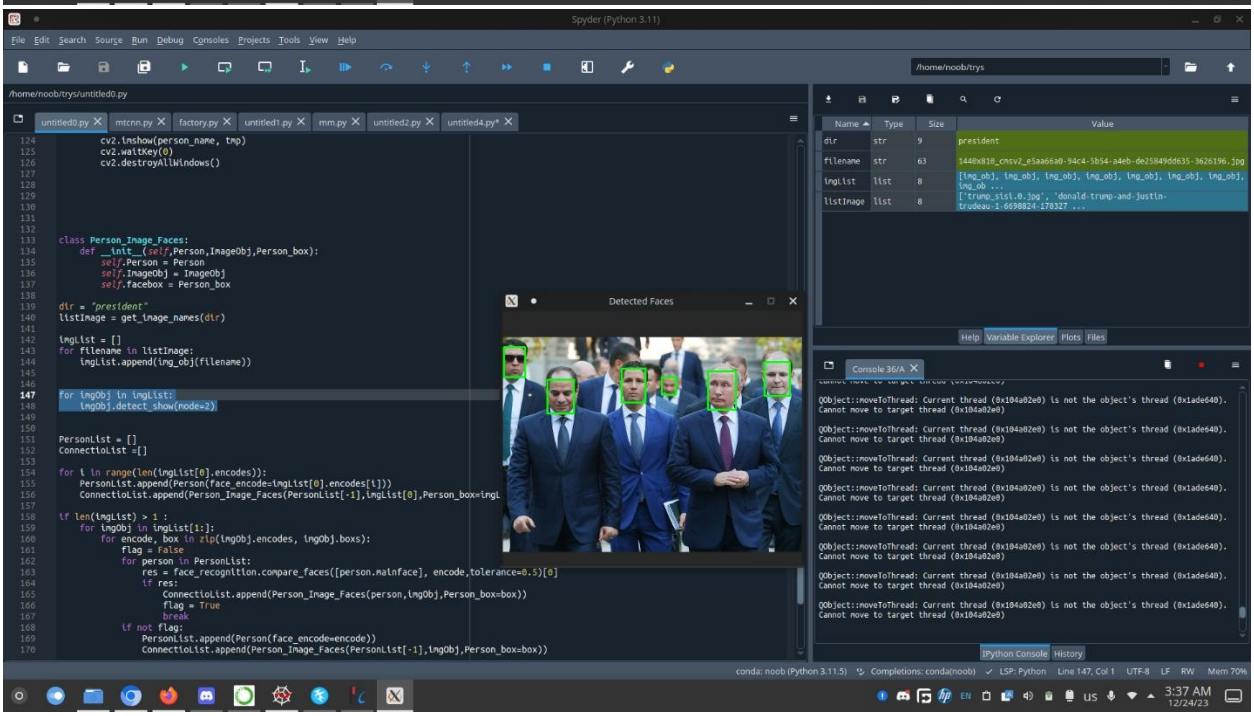
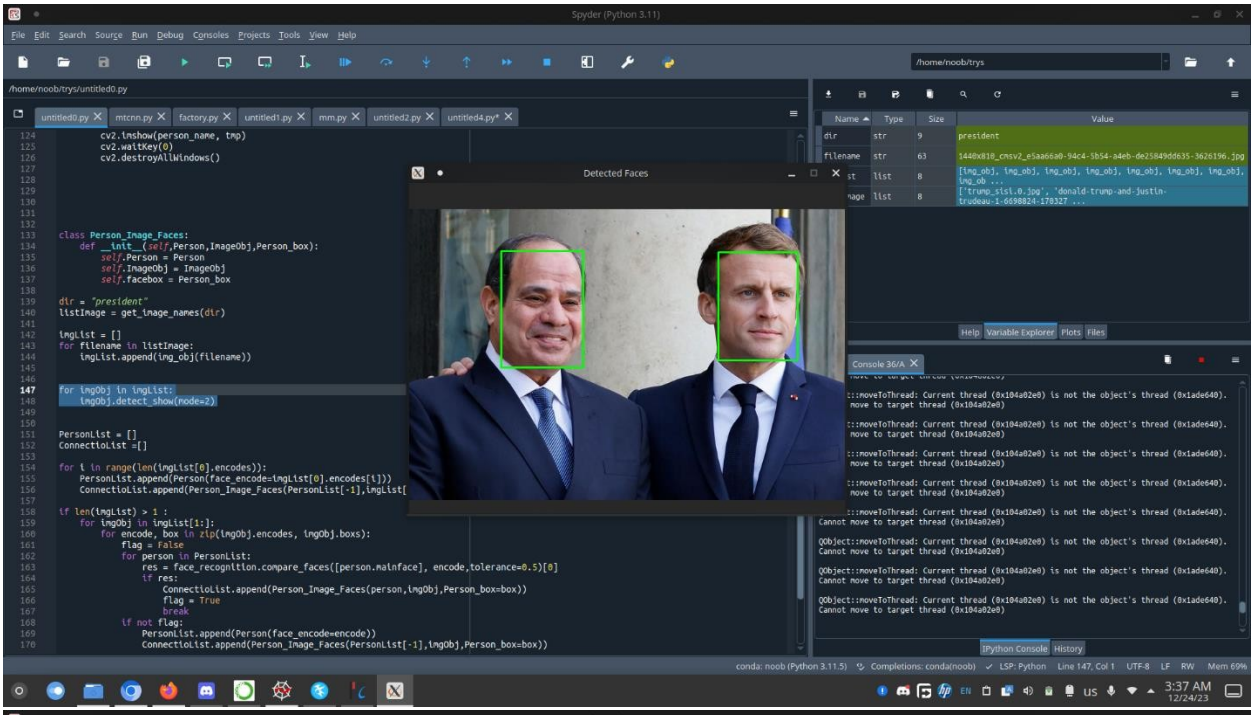
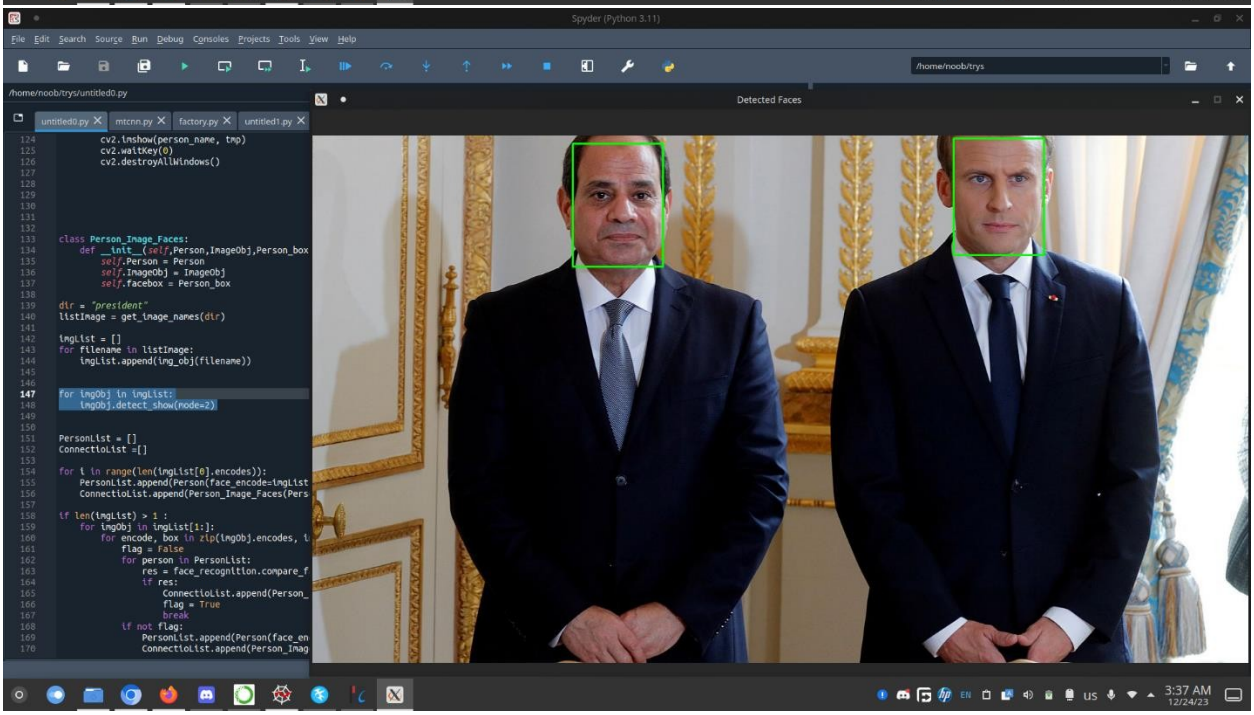
self.Person = Person
self.ImageObj = ImageObj
self.facebox = Person_box
dir = "president"
listImage = get_image_names(dir)
imgList = []
for filename in listImage:
imgList.append(img_obj(filename))
for imgObj in imgList:
imgObj.detect_show(node=2)
PersonList = []
ConnectioList =[]
for i in range(len(imgList[0].encodes)):
PersonList.append(Person(face_encode=imgList[0].encodes[i]))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgList[0],Person_box=imgL
if len(imgList) > 1 :
for imgObj in imgList[1:]:
for encode, box in zip(imgObj.encodes, imgObj.boxs):
flag = False
for person in PersonList:
res = face_recognition.compare_faces([person.mainface], encode,tolera
if res:
ConnectioList.append(Person_Image_Faces(person,imgObj,Person_box=
flag = True
break
if not flag:
PersonList.append(Person(face_encode=encode))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgObj,Person_box=box))
Name Type Size Value
dir str 9 president
filename str 63 1440x810_cnsv2_e5aa66a0-94c4-5b54-a4eb-de25849dd635-3626196.jpg
imgList list 8 [img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_ob ...
listImage list 8 ['trump_sisi.0.jpg', 'donald-trump-and-justin-trudeau-1-6698824-178327 ...
Detected Faces
Help Variable Explorer Plots Files
: Current thread (0x104a02e0) is not the object's thread (0x1ade640).
thread (0x104a02e0)
QObject::moveToThread: Current thread (0x104a02e0) is not the object's thread (0x1ade640).
Cannot move to target thread (0x104a02e0)
IPython Console History
conda: noob (Python 3.11.5) Completions: conda(noob) LSP: Python Line 147, Col 1 UTF-8 LF RW Mem 70%
3:36 AM
12/24/23


Spyder (Python 3.11)
File Edit Search Source Run Debug Consoles Projects Tools View Help
/home/noob/trys
/home/noob/trys/untitled0.py
untitled0.py
mtcnn.py
factory.py
untitled1.py
mm.py
untitled2.py
untitled4.py*
cv2.imshow(person_name, tmp)
cv2.waitKey(0)
cv2.destroyAllWindows()
class Person_Image_Faces:
def __init__(self,Person,ImageObj,Person_box):
self.Person = Person
self.ImageObj = ImageObj
self.facebox = Person_box
dir = "president"
listImage = get_image_names(dir)
imgList = []
for filename in listImage:
imgList.append(img_obj(filename))
for imgObj in imgList:
imgObj.detect_show(node=2)
PersonList = []
ConnectioList =[]
for i in range(len(imgList[0].encodes)):
PersonList.append(Person(face_encode=imgList[0].encodes[i]))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgList[0],Person_b
if len(imgList) > 1 :
for imgObj in imgList[1:]:
for encode, box in zip(imgObj.encodes, imgObj.boxs):
flag = False
for person in PersonList:
res = face_recognition.compare_faces([person.mainface], encode
if res:
ConnectioList.append(Person_Image_Faces(person,imgObj,Pers
flag = True
break
if not flag:
PersonList.append(Person(face_encode=encode))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgObj,
Name Type Size Value
dir str 9 president
filename str 63 1440x810_cmsv2_e5aa66a0-94c4-5b54-a4eb-de25849dd635-3626196.jpg
Detected Faces
© AFP/P. Galovich
3:37 AM
12/24/23


Spyder (Python 3.11)
File Edit Search Source Run Debug Consoles Projects Tools View Help
/home/noob/trys
/home/noob/trys/untitled0.py
untitled0.py
mtcnn.py
factory.py
untitled1.py
mm.py
untitled2.py
untitled4.py*
cv2.imshow(person_name, tmp)
cv2.waitKey(0)
cv2.destroyAllWindows()
class Person_Image_Faces:
def __init__(self,Person,ImageObj,Person_box):
self.Person = Person
self.ImageObj = ImageObj
self.facebox = Person_box
dir = "president"
listImage = get_image_names(dir)
imgList = []
for filename in listImage:
imgList.append(img_obj(filename))
for imgObj in imgList:
imgObj.detect_show(node=2)
PersonList = []
ConnectioList =[]
for i in range(len(imgList[0].encodes)):
PersonList.append(Person(face_encode=imgList[0].encodes[i]))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgList[0],Person_box=img
if len(imgList) > 1 :
for imgObj in imgList[1:]:
for encode, box in zip(imgObj.encodes, imgObj.boxs):
flag = False
for person in PersonList:
res = face_recognition.compare_faces([person.mainface], encode,tolerance=0.5)[0]
if res:
ConnectioList.append(Person_Image_Faces(person,imgObj,Person_box=box))
flag = True
break
if not flag:
PersonList.append(Person(face_encode=encode))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgObj,Person_box=box))
Detected Faces
Name Type Size Value
dir str 9 president
filename str 63 1440x810_cmsv2_e5aa66a0-94c4-5b54-a4eb-de25849dd635-3626196.jpg
imgList list 8 [img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_ob ...
listImage list 8 ['trump_sisi.0.jpg', 'donald-trump-and-justin-trudeau-1-6698824-178327 ...
Help Variable Explorer Plots Files
Console 36/A
QObject::moveToThread: Current thread (0x104a02e0) is not the object's thread (0x1ade640).
Cannot move to target thread (0x104a02e0)
IPython Console History
conda: noob (Python 3.11.5) Completions: conda(noob) LSP: Python Line 147, Col 1 UTF-8 LF RW Mem 70%
3:37 AM
12/24/23

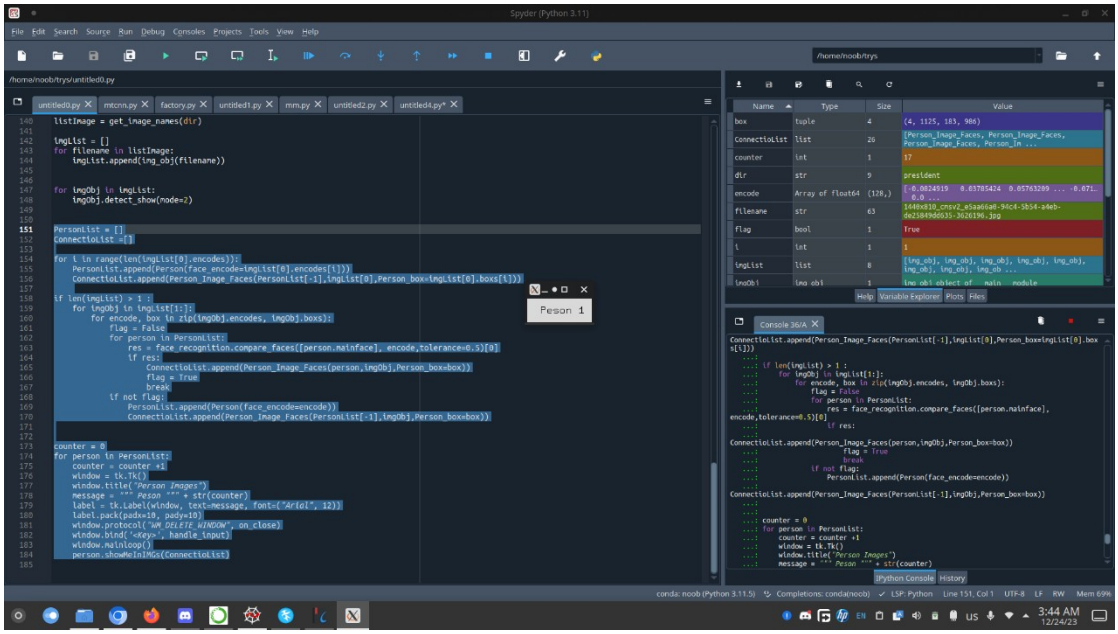

Spyder (Python 3.11)
File Edit Search Source Run Debug Consoles Projects Tools View Help
/home/noob/trys
/home/noob/trys/untitled0.py
untitled0.py
mtcnn.py
factory.py
untitled1.py
mm.py
untitled2.py
untitled4.py*
Detected Faces
Name Type Size Value
dir str 9 president
filename str 63 1440x810_cmsv2_e5aa66a0-94c4-5b54-a4eb-de25849dd635-3626196.jpg
st list 8 [img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_ob ...
nage list 8 ['trump_sisi.0.jpg', 'donald-trump-and-justin-trudeau-1-6698824-378327 ...
Help Variable Explorer Plots Files
Console 36/A
IPython Console History
conda: noob (Python 3.11.5) Completions: conda(noob) LSP: Python Line 147, Col 1 UTF-8 LF RW Mem 69%
3:37 AM
12/24/23

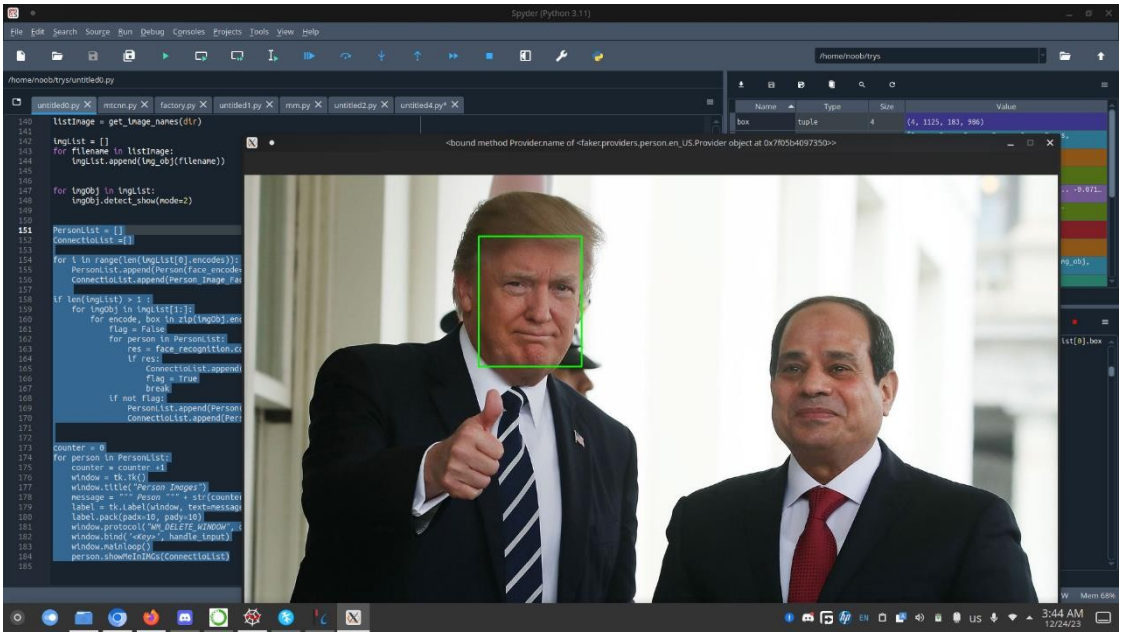

Spyder (Python 3.11)
File Edit Search Source Run Debug Consoles Projects Tools View Help
/home/noob/trys
/home/noob/trys/untitled0.py
Detected Faces
3:37 AM
12/24/23

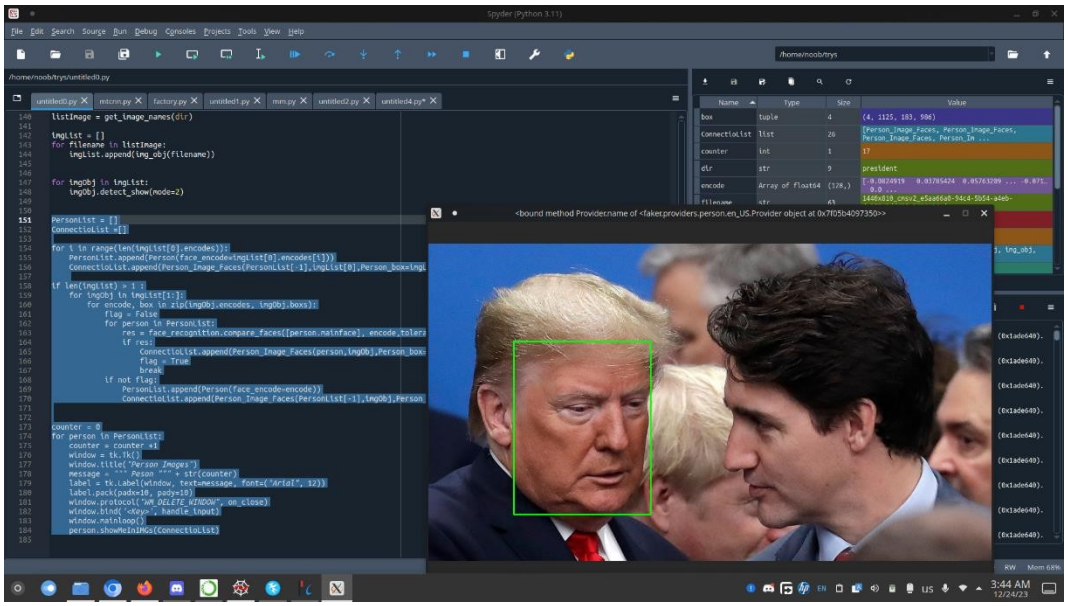
Recognition:

- Get person's picture where her appeared in it:

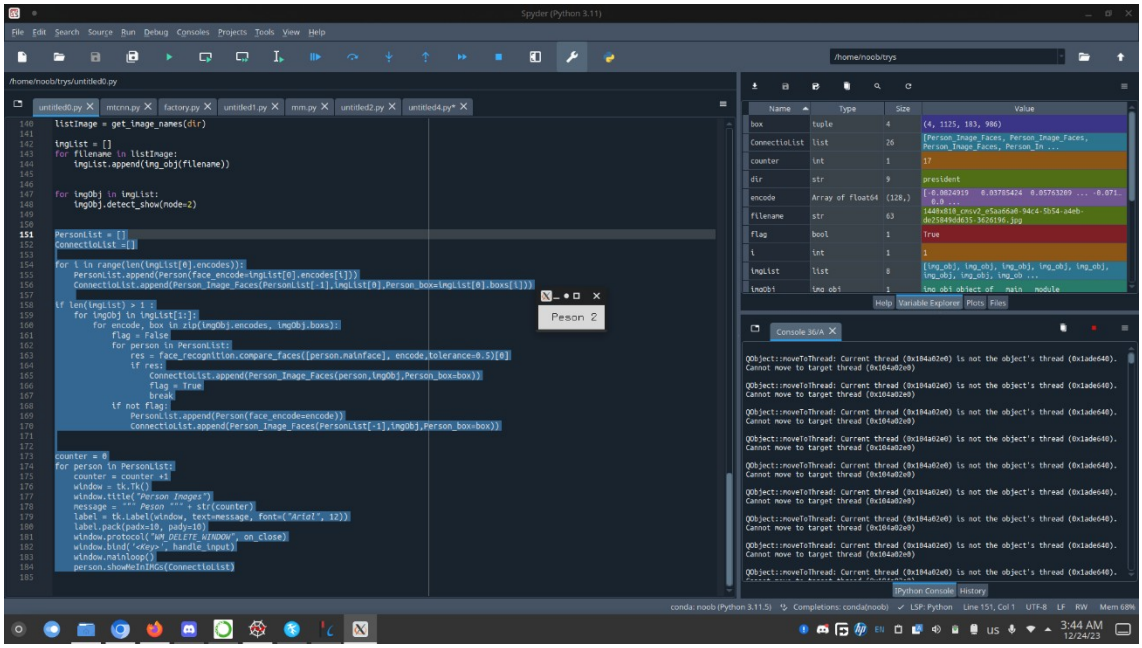
1. Person one:

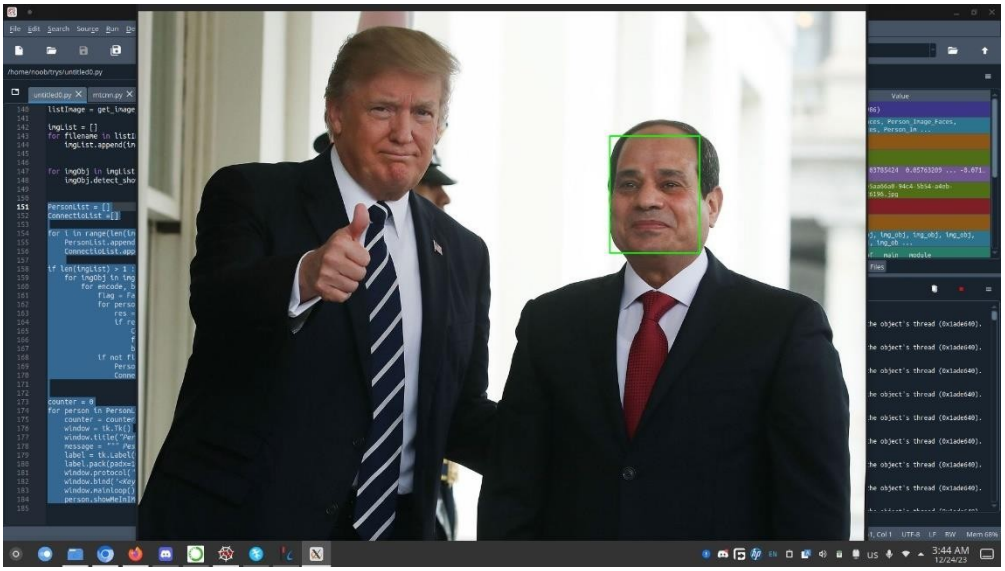


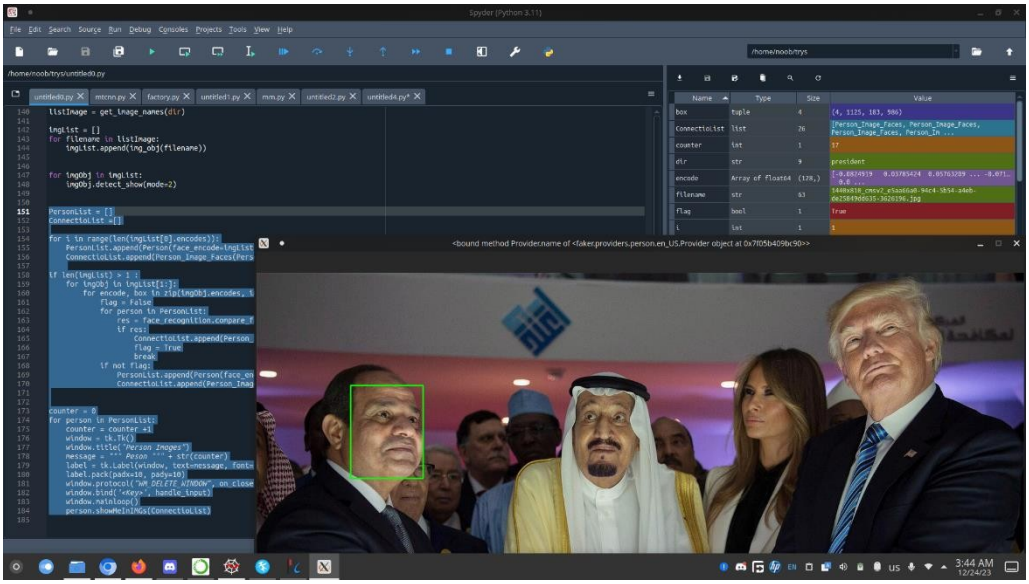


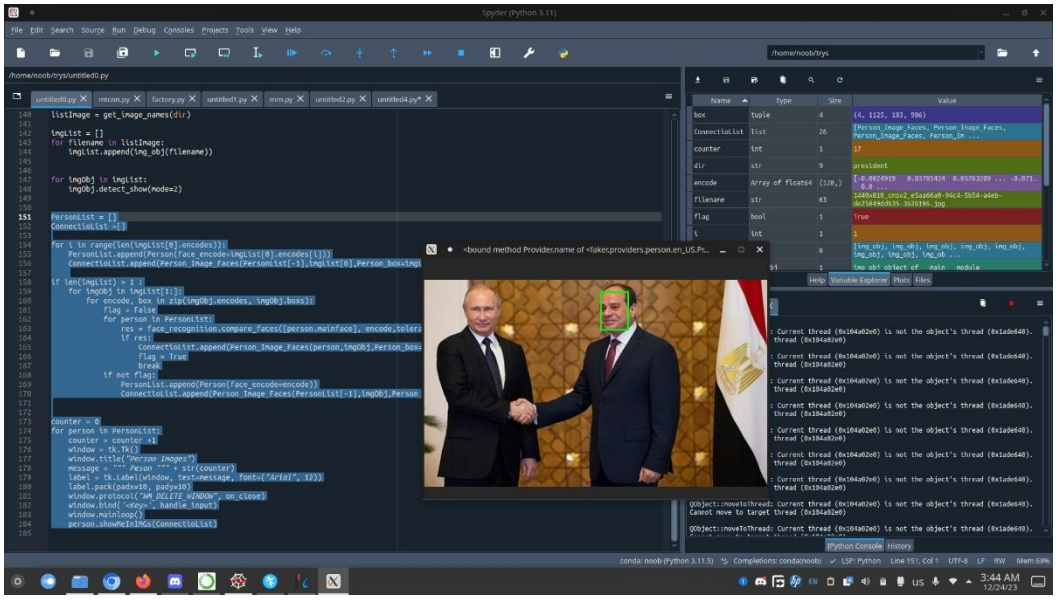


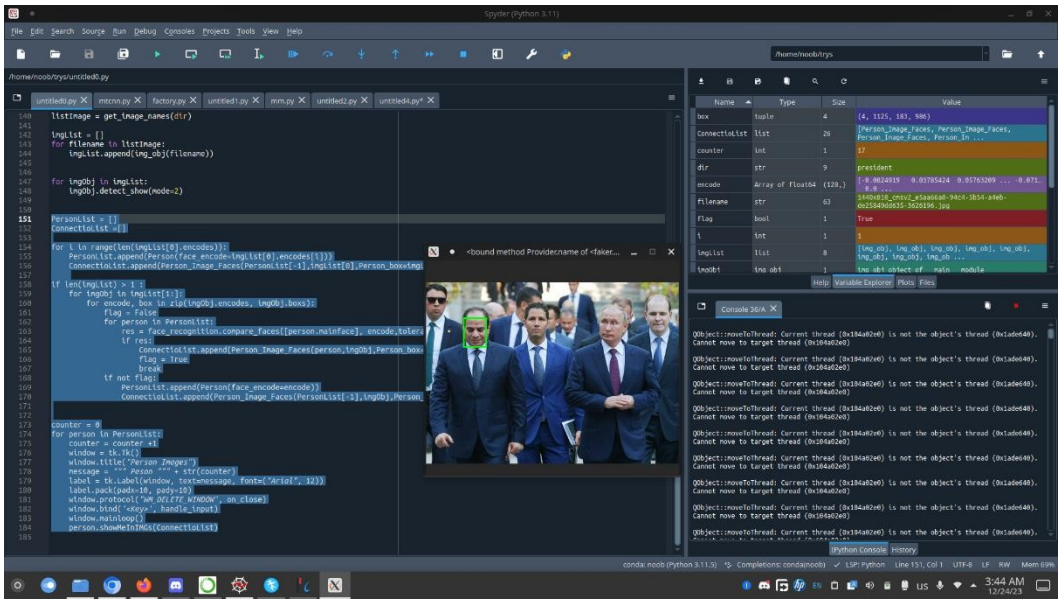
2. Person two:

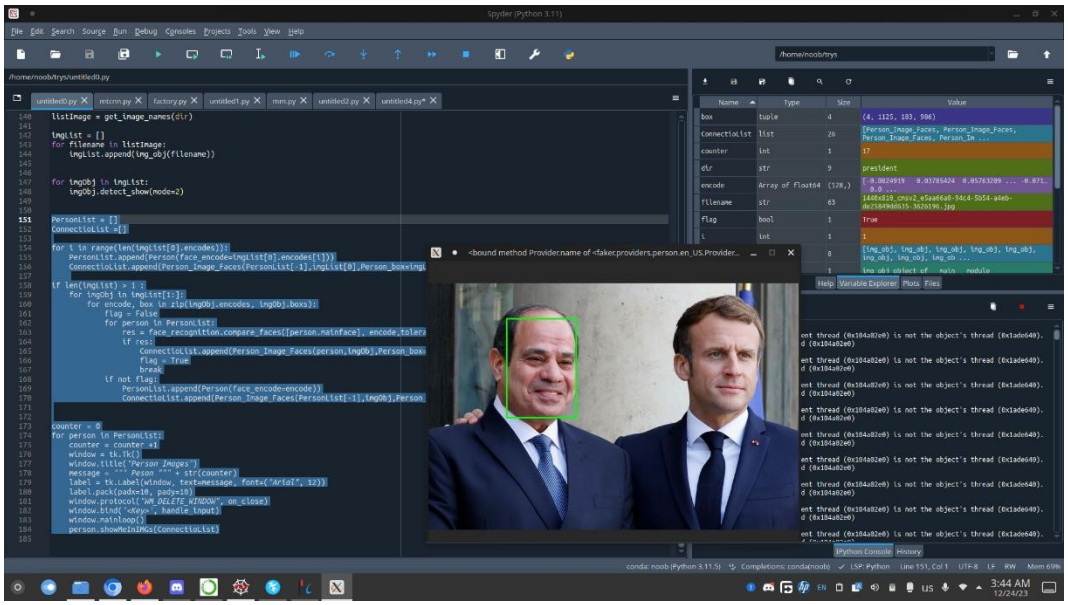


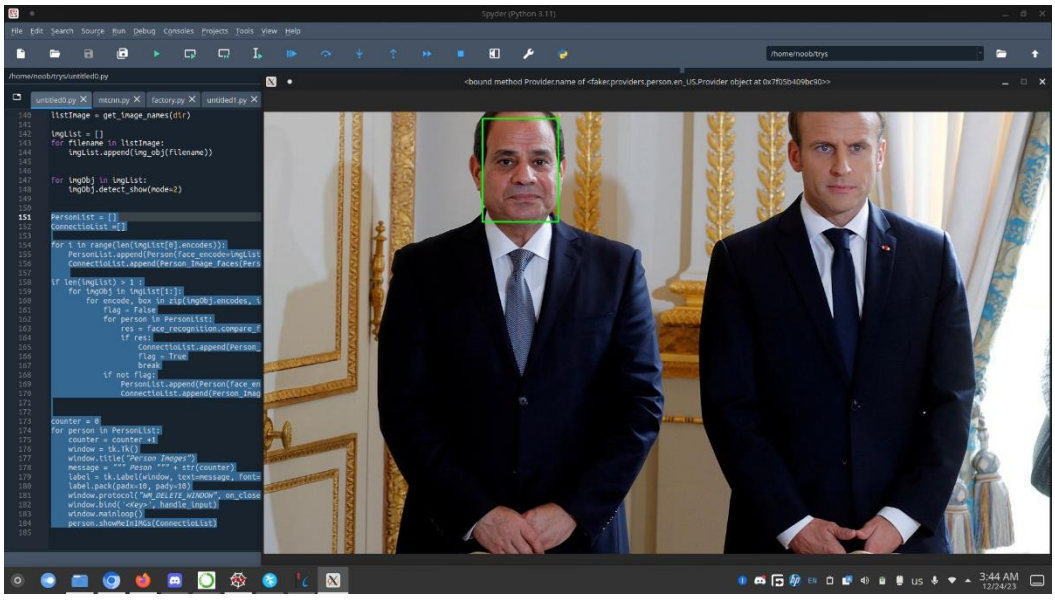




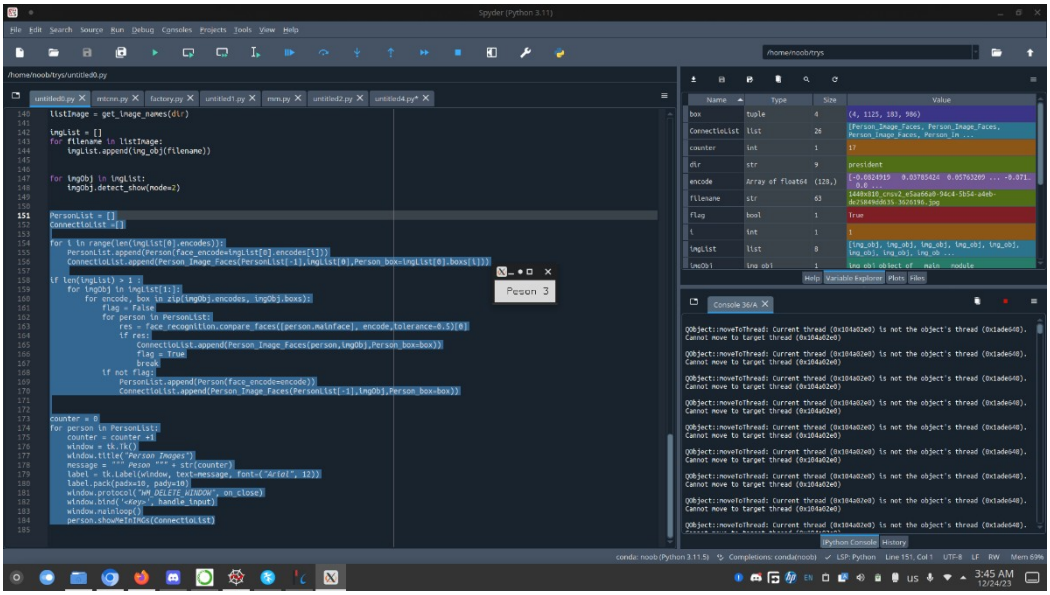


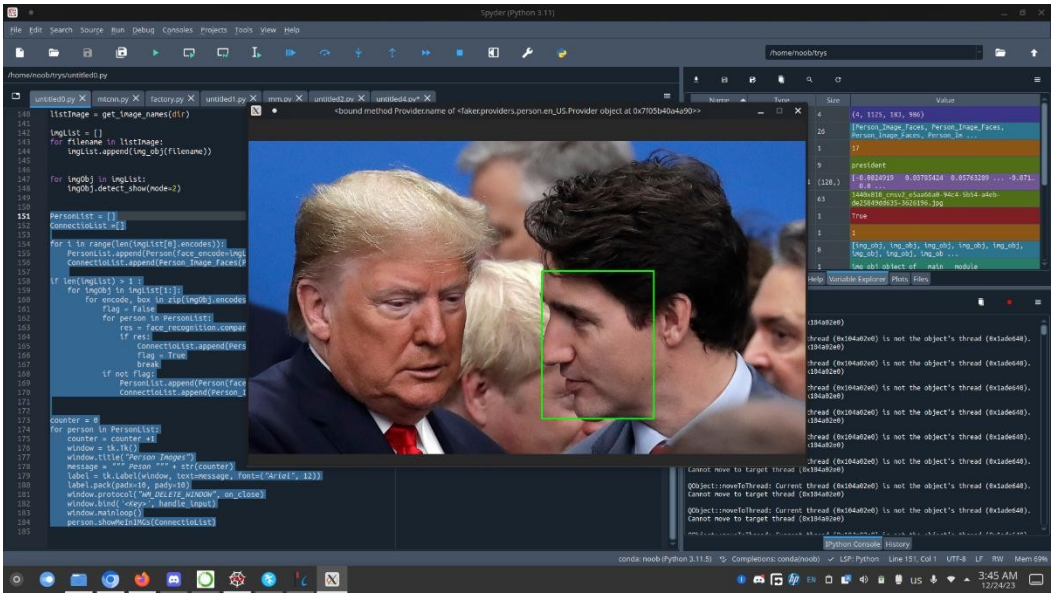

Spyder (Python 3.11)
File Edit Search Source Run Debug Consoles Projects Tools View Help
/home/noob/trys
/home/noob/trys/untitled0.py
untitled0.py mtcnn.py factory.py untitled1.py mm.py untitled2.py untitled4.py*
listImage = get_image_names(dir)
imgList = []
for filename in listImage:
imgList.append(img_obj(filename))
for imgObj in imgList:
imgObj.detect_show(mode=2)
PersonList = []
ConnectioList =[]
for i in range(len(imgList[0].encodes)):
PersonList.append(Person(face_encode=imgList[0].encodes[i]))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgList[0],Person_box=img
if len(imgList) > 1 :
for imgObj in imgList[1:]:
for encode, box in zip(imgObj.encodes, imgObj.boxs):
flag = False
for person in PersonList:
res = face_recognition.compare_faces([person.mainface], encode,toler
if res:
ConnectioList.append(Person_Image_Faces(person,imgObj,Person_box
flag = True
break
if not flag:
PersonList.append(Person(face_encode=encode))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgObj,Person
counter = 0
for person in PersonList:
counter = counter +1
window = tk.Tk()
window.title('Person Images')
message = """ Person """+ str(counter)
label = tk.Label(window, text=message, font=('Arial', 12))
label.pack(padx=10, pady=10)
window.protocol("WM_DELETE_WINDOW", on_close)
window.bind('<Key>', handle_input)
window.mainloop()
person.showMeInIMGs(ConnectioList)
<bound method Provider.name of <faker...
Name Type Size Value
box tuple 4 (4, 1125, 183, 986)
ConnectioList list 26 [Person_Image_Faces, Person_Image_Faces, Person_Image_Faces, Person_In ...
counter int 1 17
dir str 9 president
encode Array of float64 (128,) [-0.0824919 0.03785424 0.05763289 ... -0.071... 0.0 ...
filename str 63 1440x810_cmsv2_e5aa66a0-94c4-3b54-a4eb-de2584900655-3026196.jpg
flag bool 1 True
i int 1 1
imgList list 8 [img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_ob ...
imgObj img_obj 1 img_obj object of __main__ module
Console 36/A
QObject::moveToThread: Current thread (0x184a02e0) is not the object's thread (0x1ade640).
Cannot move to target thread (0x184a02e0)
IPython Console History
conda: noob (Python 3.11.5) Completions: conda(noob) LSP: Python Line 151, Col 1 UTF-8 LF RW Mem 69%
3:44 AM
12/24/23


Spyder (Python 3.11)
File Edit Search Source Run Debug Consoles Projects Tools View Help
/home/noob/trys
/home/noob/trys/untitled0.py
untitled0.py mtcnn.py factory.py untitled1.py mm.py untitled2.py untitled4.py*
listImage = get_image_names(dir)
imgList = []
for filename in listImage:
imgList.append(img_obj(filename))
for imgObj in imgList:
imgObj.detect_show(mode=2)
PersonList = []
ConnectioList =[]
for i in range(len(imgList[0].encodes)):
PersonList.append(Person(face_encode=imgList[0].encodes[i]))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgList[0],Person_box=img
if len(imgList) > 1 :
for imgObj in imgList[1:]:
for encode, box in zip(imgObj.encodes, imgObj.boxs):
flag = False
for person in PersonList:
res = face_recognition.compare_faces([person.mainface], encode,toler
if res:
ConnectioList.append(Person_Image_Faces(person,imgObj,Person_box
flag = True
break
if not flag:
PersonList.append(Person(face_encode=encode))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgObj,Person
counter = 0
for person in PersonList:
counter = counter +1
window = tk.Tk()
window.title('Person Images')
message = """ Person """ + str(counter)
label = tk.Label(window, text=message, font=('Arial', 12))
label.pack(padx=10, pady=10)
window.protocol("WM_DELETE_WINDOW", on_close)
window.bind('<Key>', handle_input)
window.mainloop()
person.showMeInIMGs(ConnectioList)
<bound method Provider.name of <faker.providers.person.en_US.Provider...
Name Type Size Value
box tuple 4 (4, 1125, 183, 986)
ConnectioList list 26 [Person_Image_Faces, Person_Image_Faces, Person_Image_Faces, Person_In ...
counter int 1 17
dir str 9 president
encode Array of float64 (128,) [-0.0824919 0.03785424 0.05763289 ... -0.071... 0.0 ...
filename str 63 1440x810_cmsv2_e5aa66a0-94c4-3b54-a4eb-de2584900655-3026196.jpg
flag bool 1 True
i int 1 1
imgList list 8 [img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_ob ...
imgObj img_obj 1 img_obj object of __main__ module
Help Variable Explorer Plots Files
IPython Console History
conda: noob (Python 3.11.5) Completions: conda(noob) LSP: Python Line 151, Col 1 UTF-8 LF RW Mem 69%
3:44 AM
12/24/23

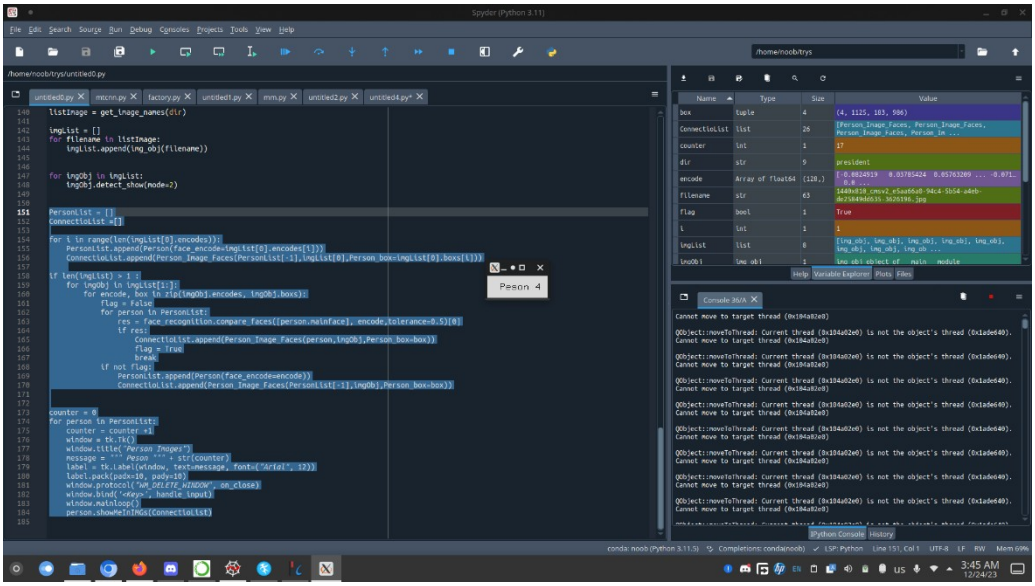

Spyder (Python 3.11)
File Edit Search Source Run Debug Consoles Projects Tools View Help
/home/noob/trys
/home/noob/trys/untitled0.py
untitled0.py mtcnn.py factory.py untitled1.py
listImage = get_image_names(dir)
imgList = []
for filename in listImage:
imgList.append(img_obj(filename))
for imgObj in imgList:
imgObj.detect_show(mode=2)
PersonList = []
ConnectioList =[]
for i in range(len(imgList[0].encodes)):
PersonList.append(Person(face_encode=imgList
ConnectioList.append(Person_Image_Faces(Pers
if len(imgList) > 1 :
for imgObj in imgList[1:]:
for encode, box in zip(imgObj.encodes, i
flag = False
for person in PersonList:
res = face_recognition.compare_f
if res:
ConnectioList.append(Person_
flag = True
break
if not flag:
PersonList.append(Person(face_en
ConnectioList.append(Person_Ima
counter = 0
for person in PersonList:
counter = counter +1
window = tk.Tk()
window.title("Person Images")
message = """ Person """ + str(counter)
label = tk.Label(window, text=message, font=
label.pack(padx=10, pady=10)
window.protocol("WM_DELETE_WINDOW", on_close
window.bind('<Key>', handle_input)
window.mainloop()
person.showMeInIMGs(ConnectioList)
<bound method Provider.name of <faker.providers.person.en_US.Provider object at 0x7f05b409bc90>>
3:44 AM
12/24/23

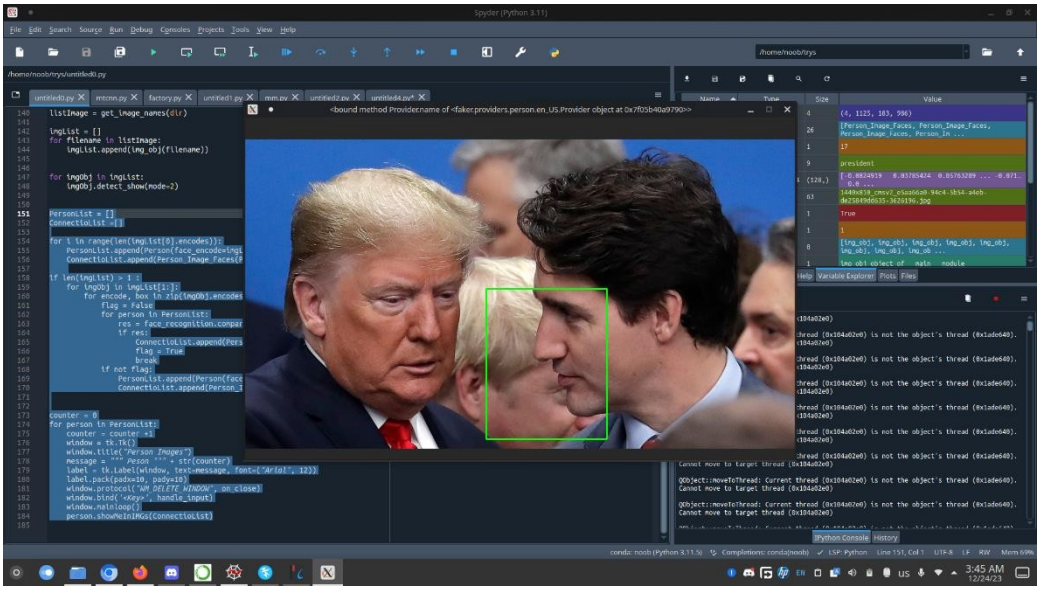
3. Person 3:





4. Person 4:





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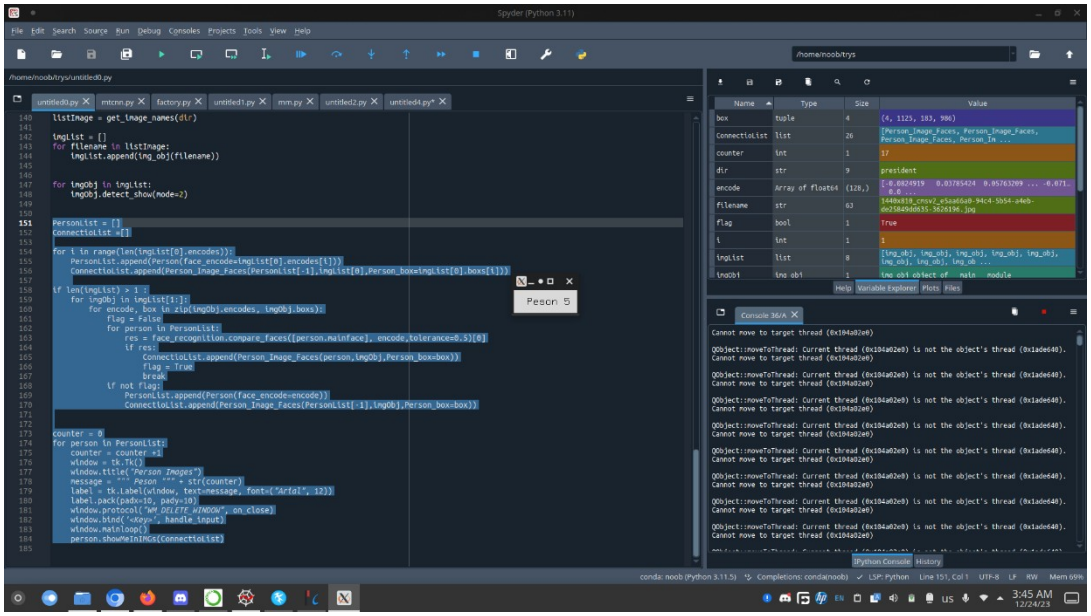

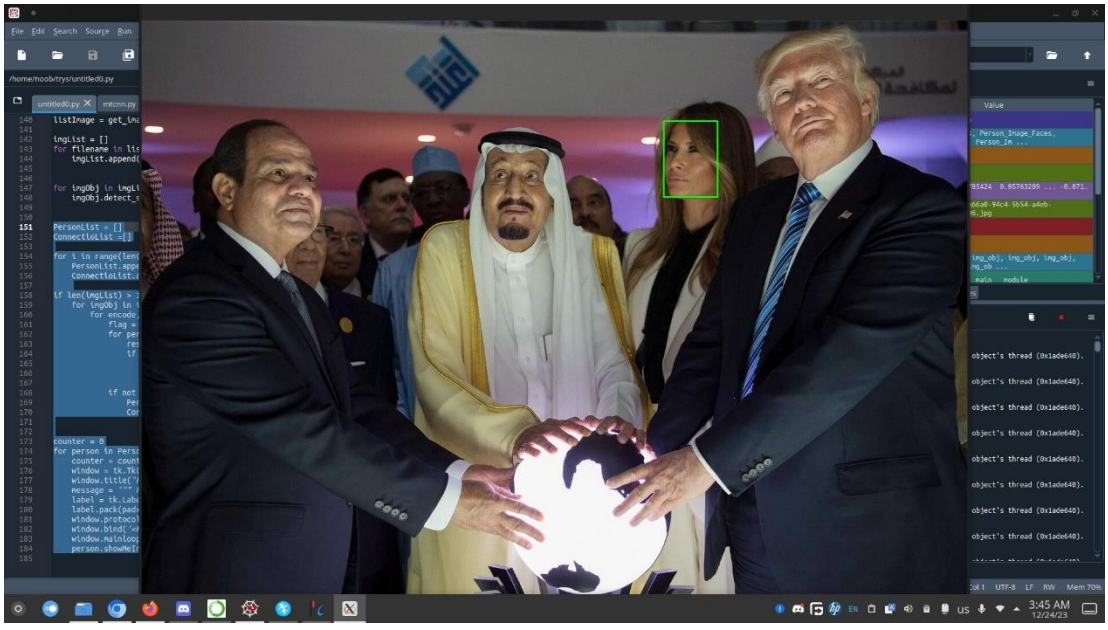

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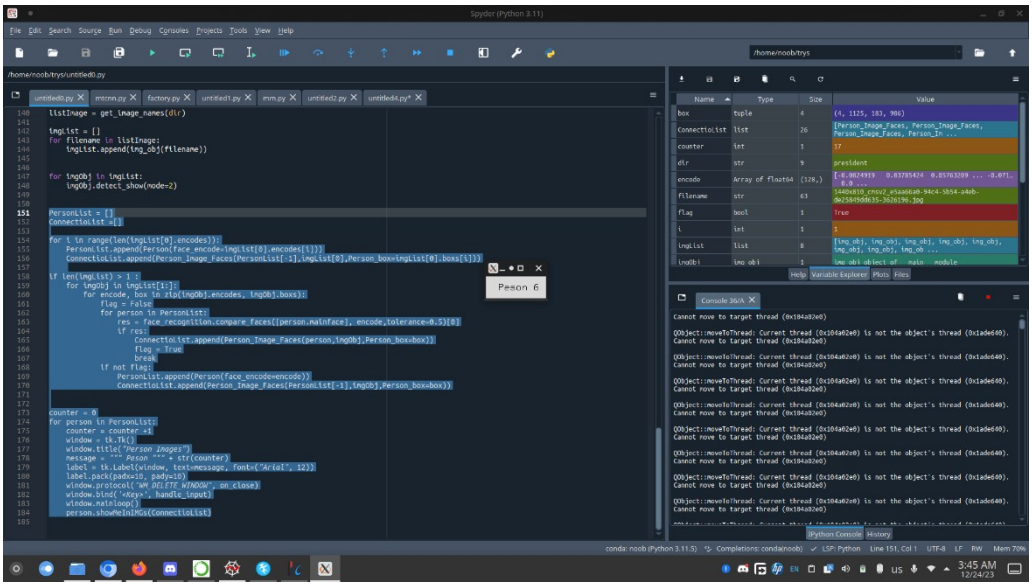

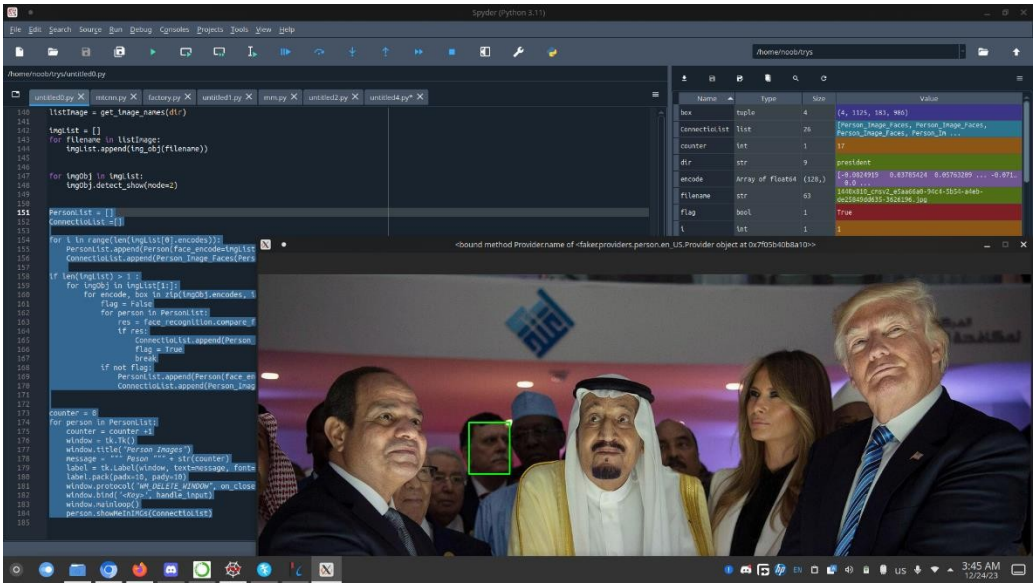

7. Person 7

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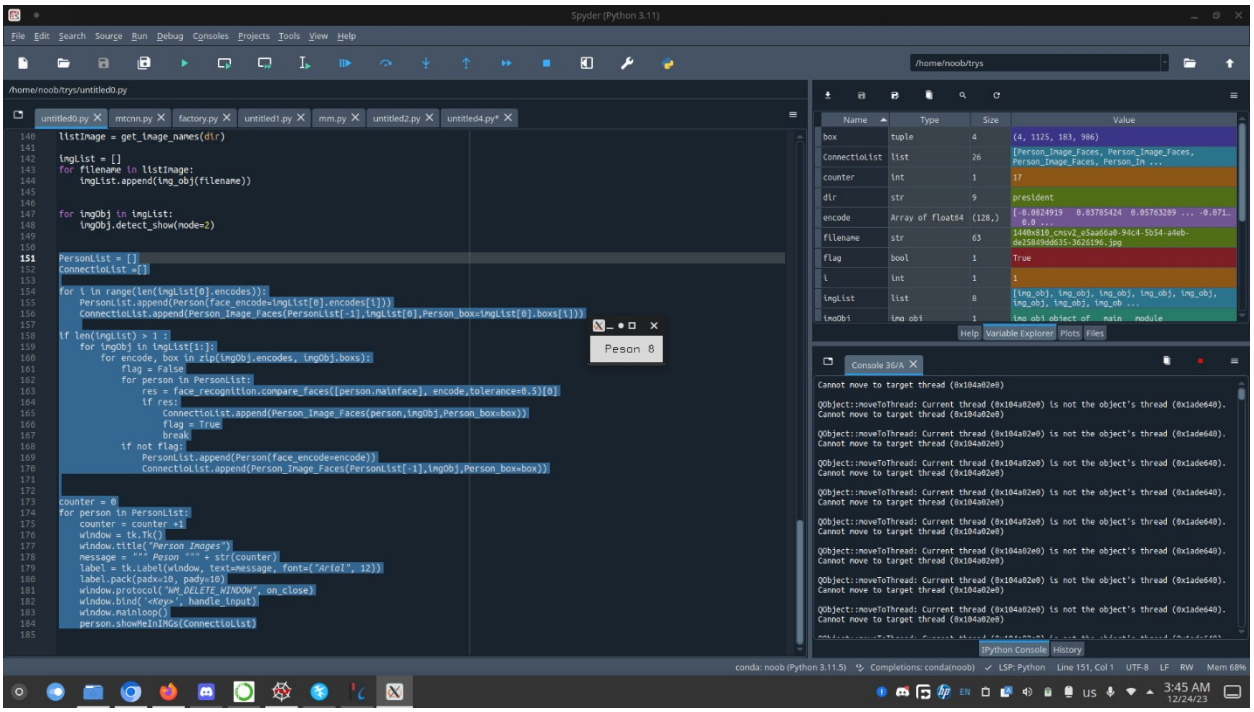

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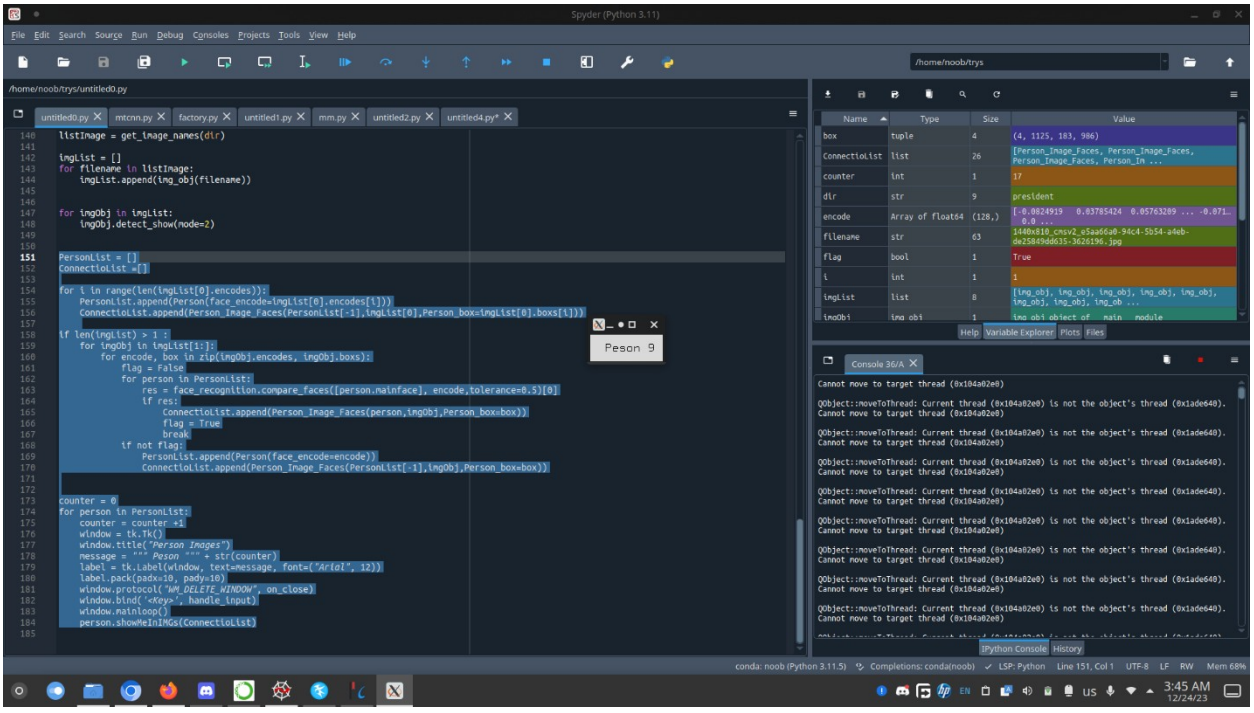

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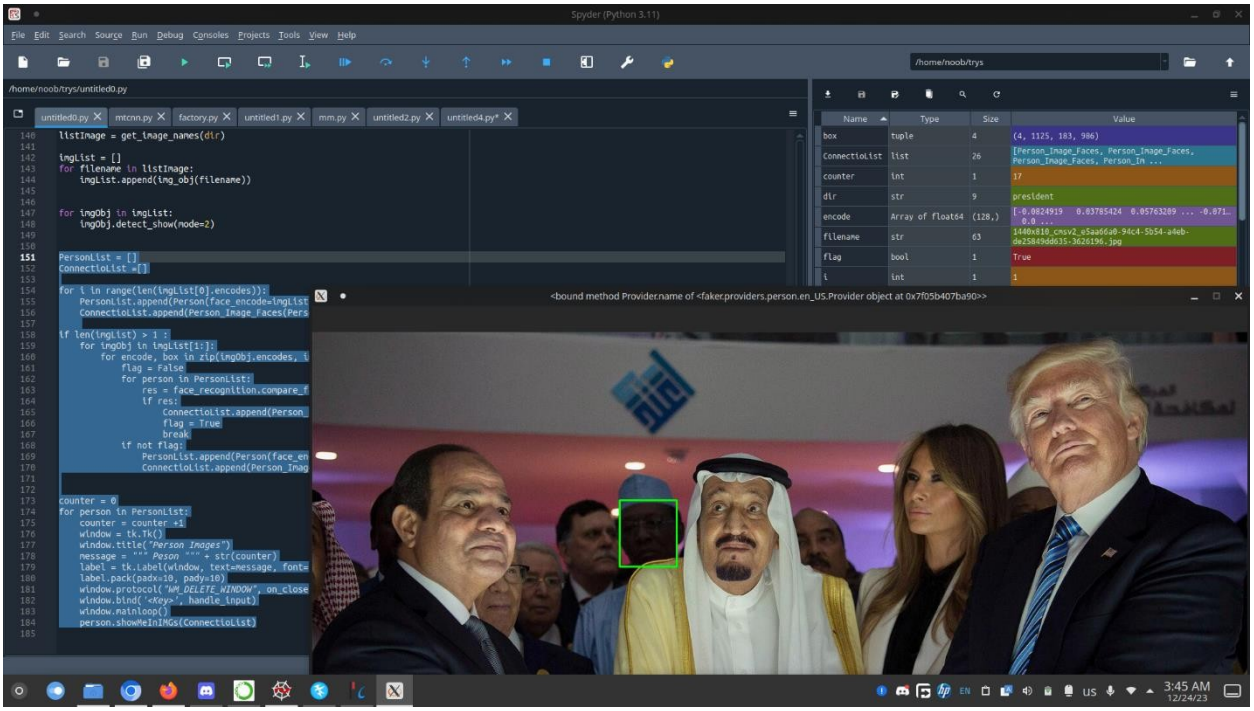
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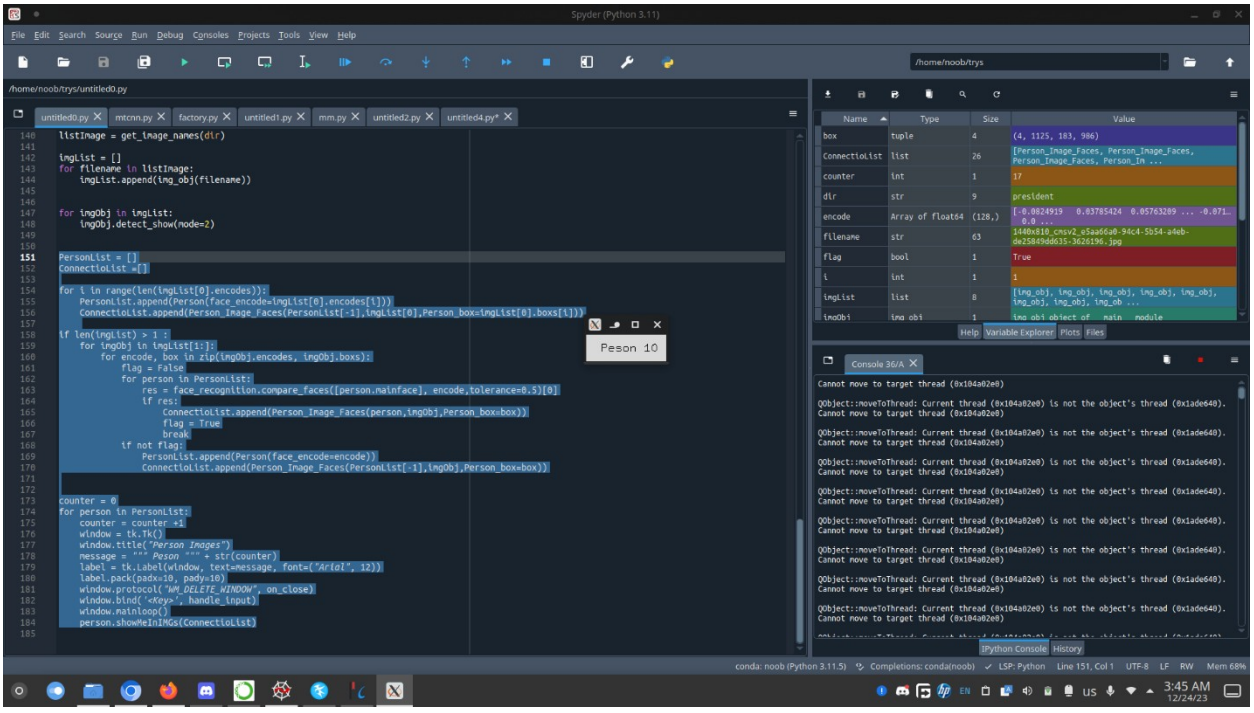
Spyder (Python 3.11)
Peson 10

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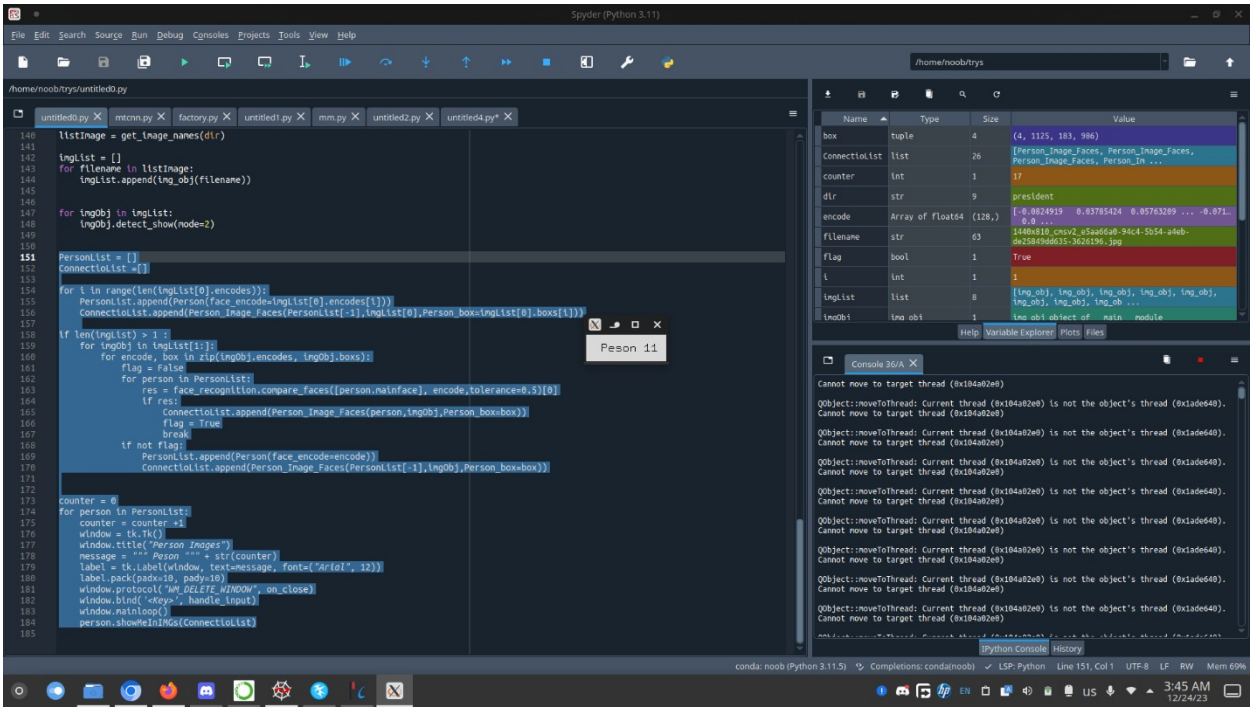
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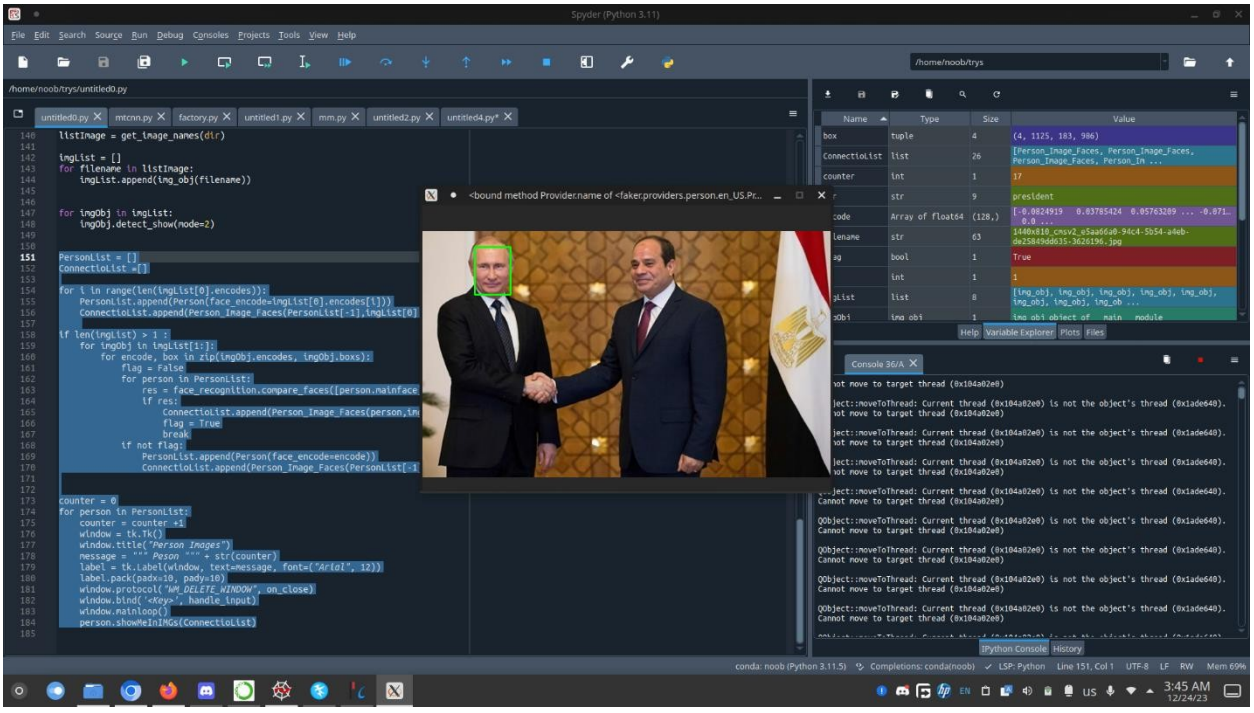
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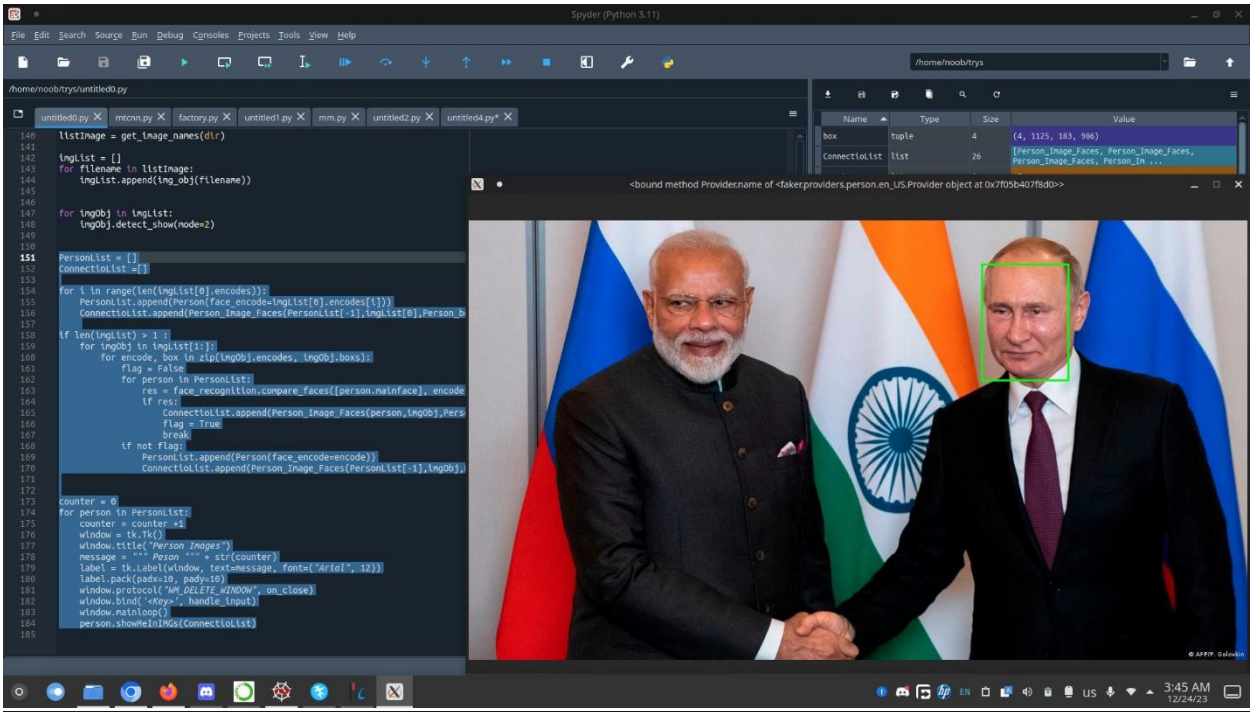
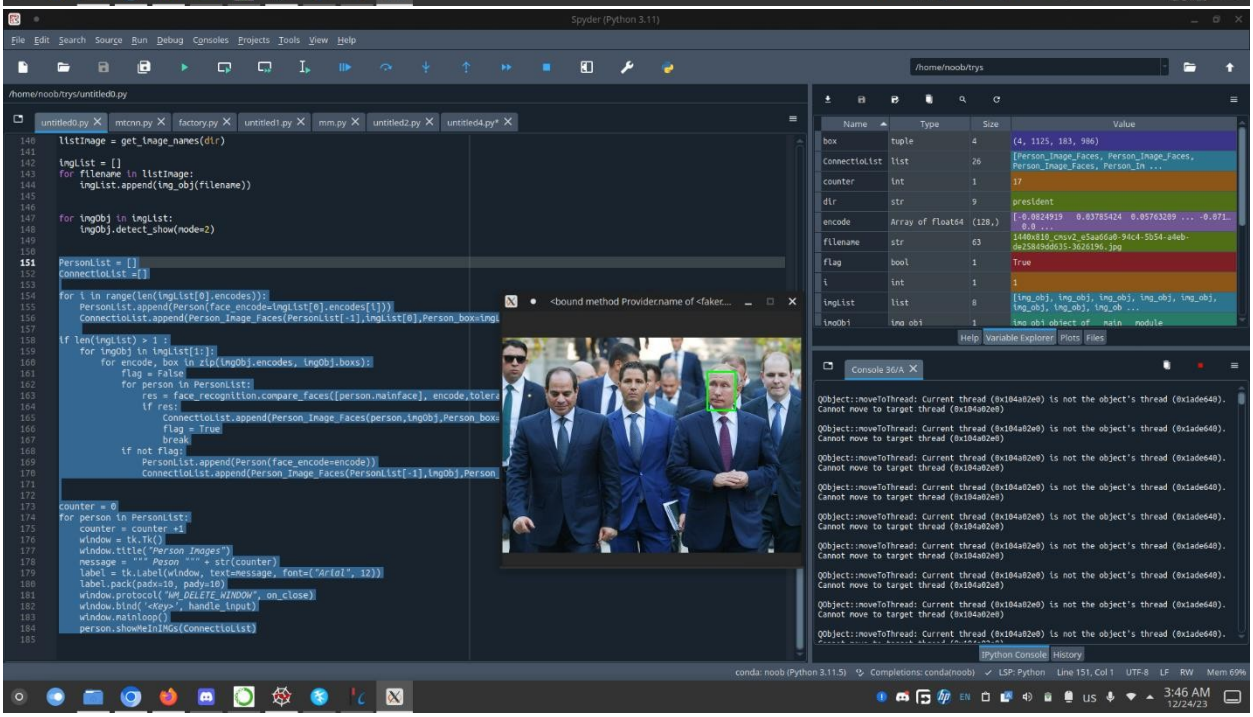
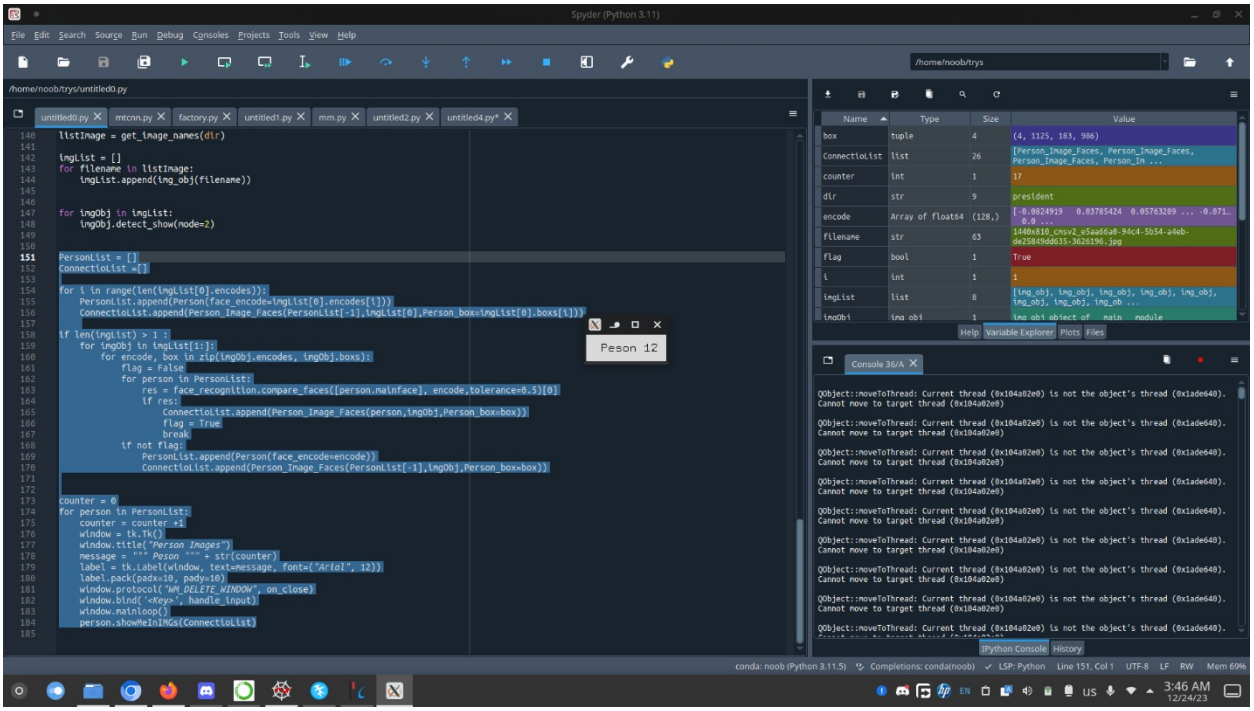
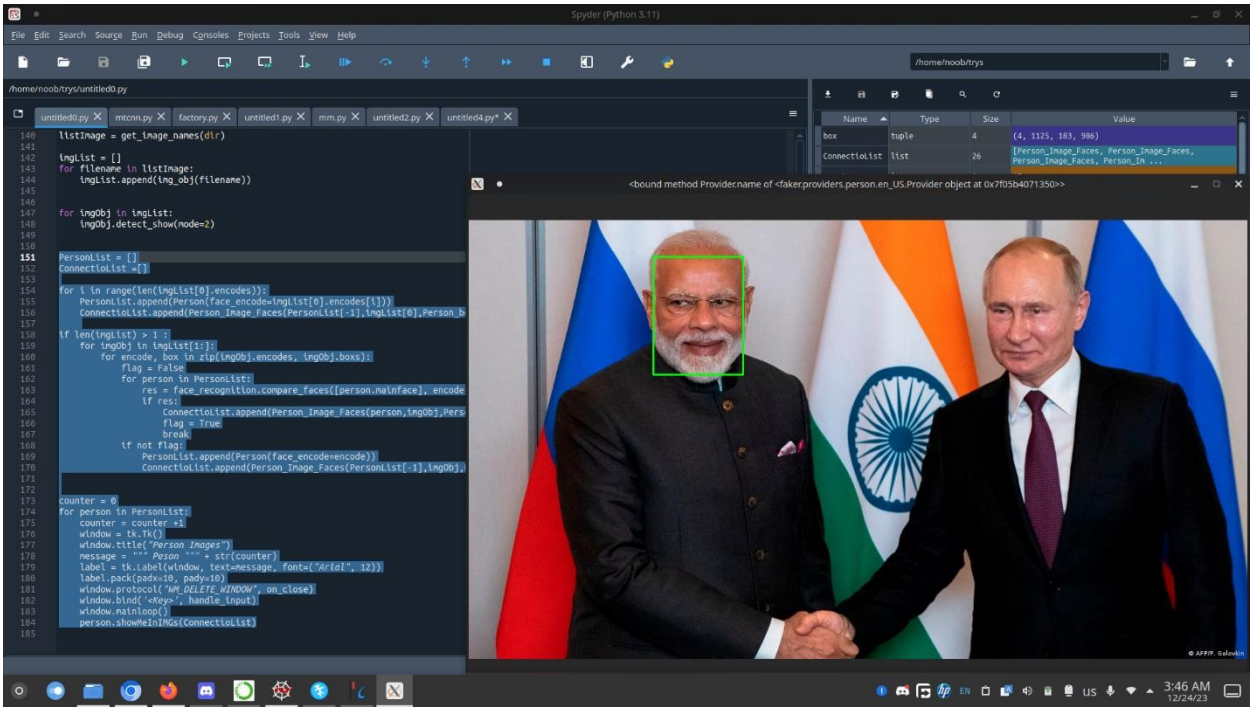

Spyder (Python 3.11)
File Edit Search Source Run Debug Consoles Projects Tools View Help
/home/noob/trys
/home/noob/trys/untitled0.py
untitled0.py
mtcnn.py
factory.py
untitled1.py
mm.py
untitled2.py
untitled4.py*
listImage = get_image_names(dlr)
imgList = []
for filename in listImage:
imgList.append(img_obj(filename))
for imgObj in imgList:
imgObj.detect_show(mode=2)
PersonList = []
ConnectioList =[]
for i in range(len(imgList[0].encodes)):
PersonList.append(Person(face_encode=imgList[0].encodes[i]))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgList[0],Person_b
if len(imgList) > 1 :
for imgObj in imgList[1:]:
for encode, box in zip(imgObj.encodes, imgObj.boxs):
flag = False
for person in PersonList:
res = face_recognition.compare_faces([person.mainface], encode
if res:
ConnectioList.append(Person_Image_Faces(person,imgObj,Pers
flag = True
break
if not flag:
PersonList.append(Person(face_encode=encode))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgObj,
counter = 0
for person in PersonList:
counter = counter +1
window = tk.Tk()
window.title("Person Images")
message = """ Person """ + str(counter)
label = tk.Label(window, text=message, font=("Arial", 12))
label.pack(padx=10, pady=10)
window.protocol("WM_DELETE_WINDOW", on_close)
window.bind('<Key>', handle_input)
window.mainloop()
person.showMeInIMGs(ConnectioList)
<bound method Provider.name of <faker.providers.person.en_US.Provider object at 0x7f05b407f8d0>>
Name Type Size Value
box tuple 4 (4, 1125, 183, 986)
ConnectioList list 26 [Person_Image_Faces, Person_Image_Faces, Person_Image_Faces, Person_In ...
© AFP/F. Galovich
3:45 AM
12/24/23

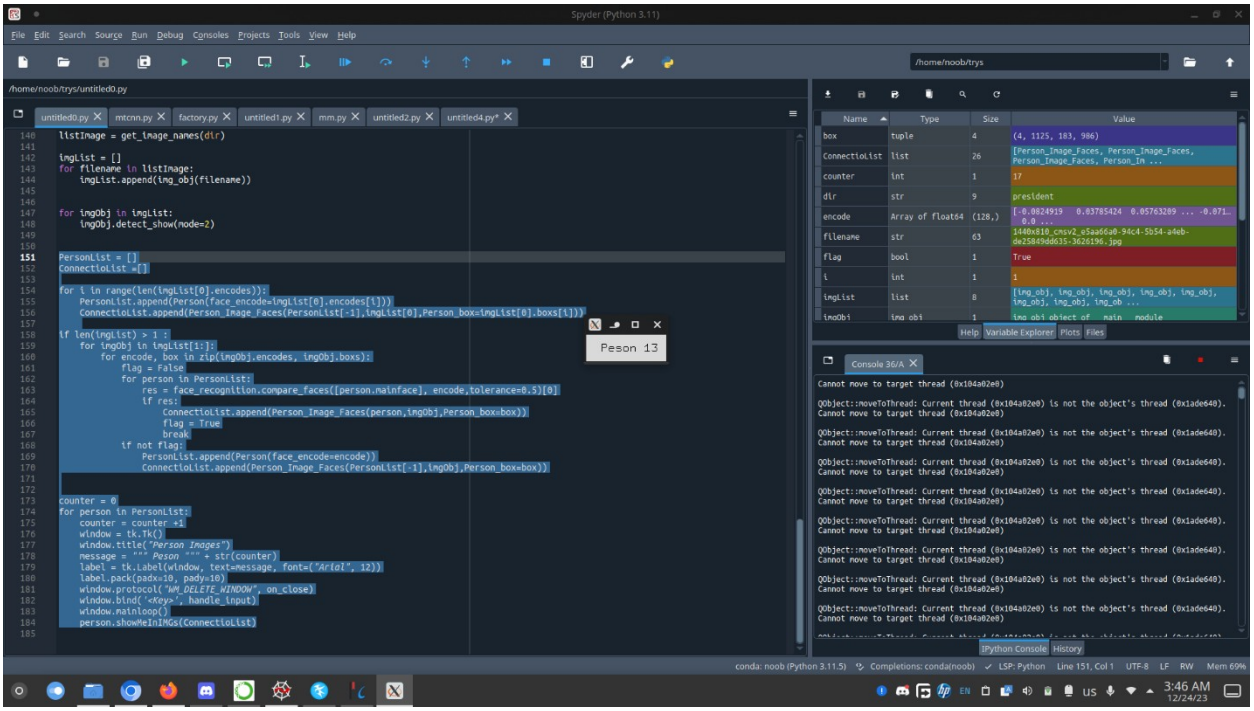

Spyder (Python 3.11)
File Edit Search Source Run Debug Consoles Projects Tools View Help
/home/noob/trys
/home/noob/trys/untitled0.py
untitled0.py
mtcnn.py
factory.py
untitled1.py
mm.py
untitled2.py
untitled4.py*
listImage = get_image_names(dlr)
imgList = []
for filename in listImage:
imgList.append(img_obj(filename))
for imgObj in imgList:
imgObj.detect_show(mode=2)
PersonList = []
ConnectioList =[]
for i in range(len(imgList[0].encodes)):
PersonList.append(Person(face_encode=imgList[0].encodes[i]))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgList[0],Person_box=imgi
if len(imgList) > 1 :
for imgObj in imgList[1:]:
for encode, box in zip(imgObj.encodes, imgObj.boxs):
flag = False
for person in PersonList:
res = face_recognition.compare_faces([person.mainface], encode,toler
if res:
ConnectioList.append(Person_Image_Faces(person,imgObj,Person_box
flag = True
break
if not flag:
PersonList.append(Person(face_encode=encode))
ConnectioList.append(Person_Image_Faces(PersonList[-1],imgObj,Person_
counter = 0
for person in PersonList:
counter = counter +1
window = tk.Tk()
window.title("Person Images")
message = """ Person """ + str(counter)
label = tk.Label(window, text=message, font=("Arial", 12))
label.pack(padx=10, pady=10)
window.protocol("WM_DELETE_WINDOW", on_close)
window.bind('<Key>', handle_input)
window.mainloop()
person.showMeInIMGs(ConnectioList)
<bound method Provider.name of <faker....
Name Type Size Value
box tuple 4 (4, 1125, 183, 986)
ConnectioList list 26 [Person_Image_Faces, Person_Image_Faces, Person_Image_Faces, Person_In ...
counter int 1 17
dlr str 9 president
encode Array of float64 (128,) [-0.0824919 0.03785424 0.05763289 ... -0.071... 0.0 ...
filename str 63 1440x810_cmsv2_e5aa66a0-94c4-5b54-a4eb-de25849dd035-3626196.jpg
flag bool 1 True
i int 1 1
imgList list 8 [img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_obj, img_ob ...
imgObj img_obj 1 img_obj object of __main__ module
Help Variable Explorer Plots Files
Console 36/A
QObject::moveToThread: Current thread (0x104a02e0) is not the object's thread (0x1ade640).
Cannot move to target thread (0x104a02e0)
IPython Console History
conda: noob (Python 3.11.5) Completions: conda(noob) LSP: Python Line 151, Col 1 UTF-8 LF RW Mem 69%
3:46 AM
12/24/23

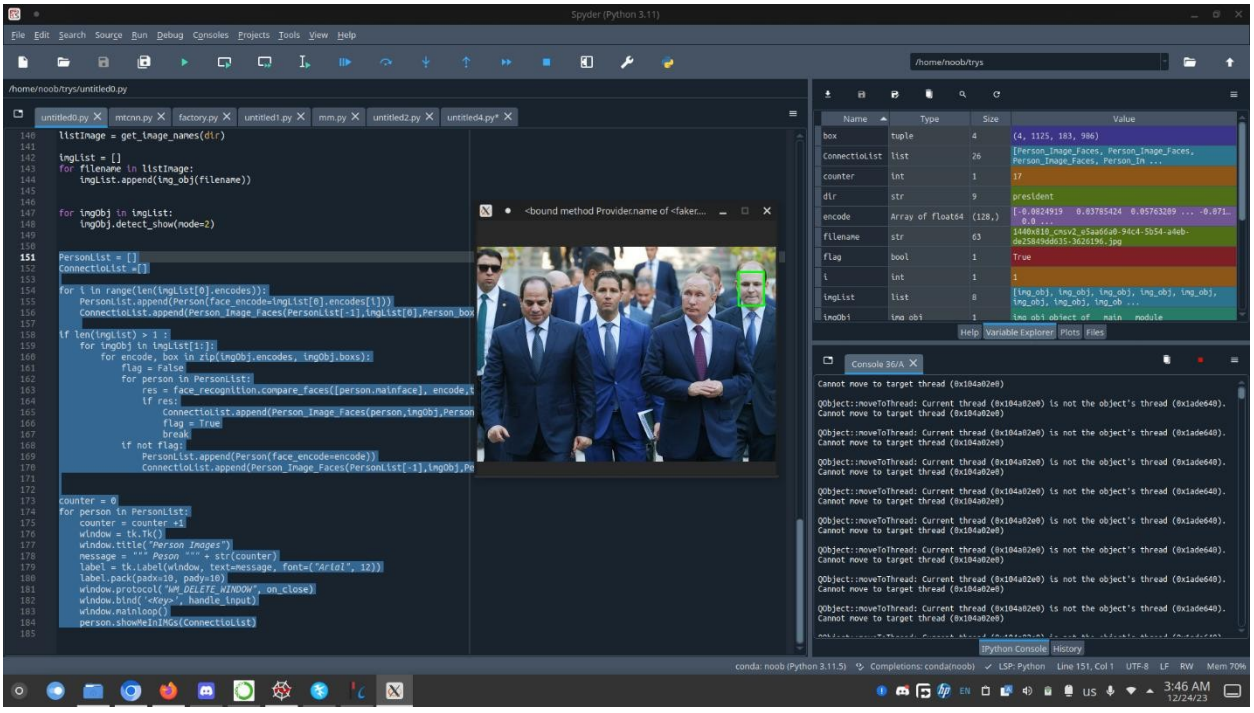
12. Person 12:


Spyder (Python 3.11)
Peson 12

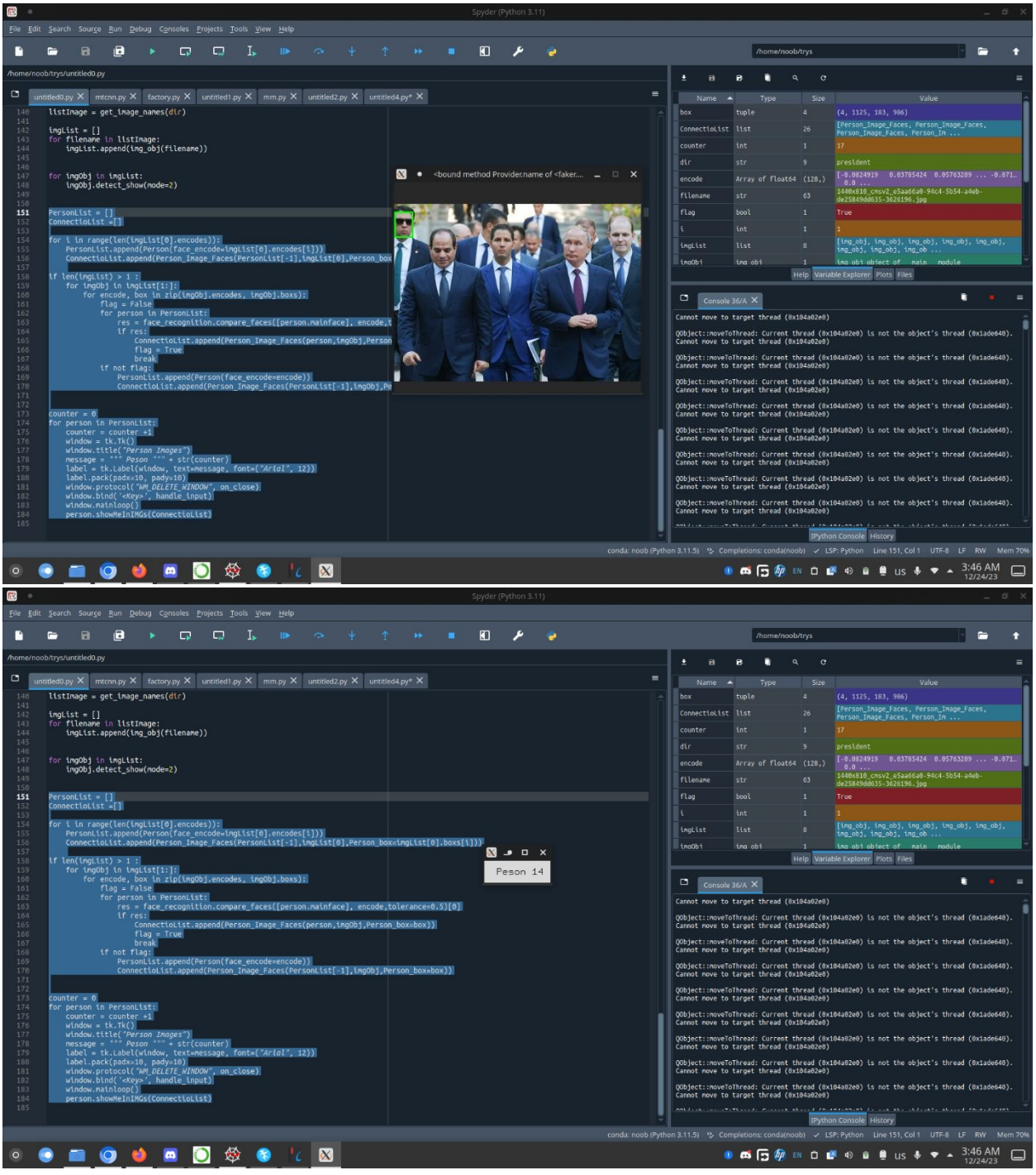

Spyder (Python 3.11)
<bound method Provider.name of <faker.providers.person.en_US.Provider object at 0x7f05b4071350>>

13. Person 13:

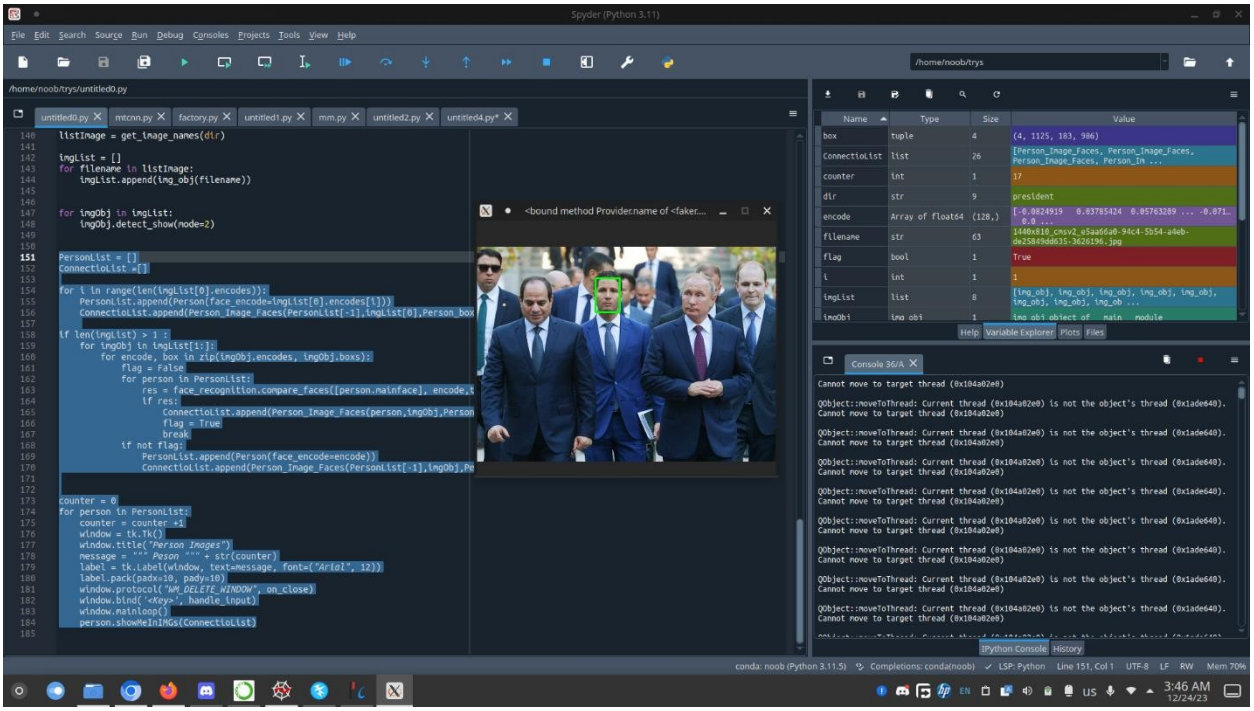

Spyder (Python 3.11)
Peson 13

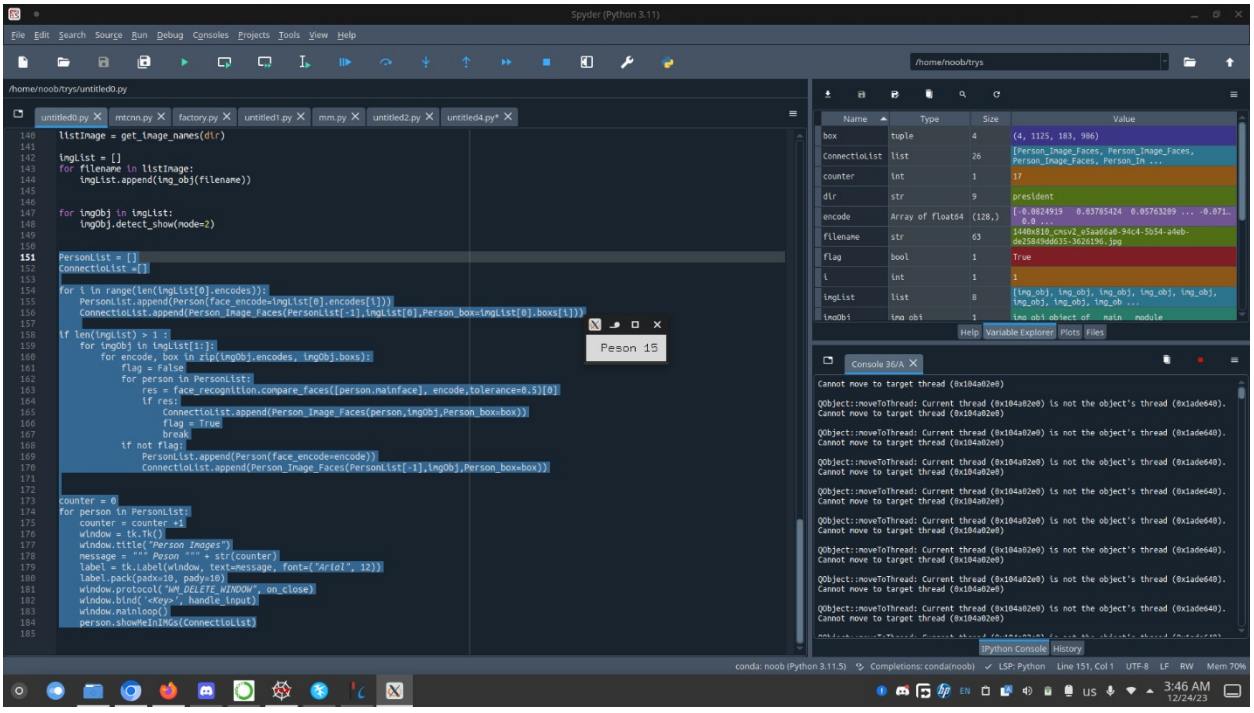

Spyder (Python 3.11)
<bound method Provider.name of <faker...

14. Person 14:



15. Person 15:


Spyder (Python 3.11)
<bound method Provider.name of <faker....
Console 36/A
Cannot move to target thread (0x104a02e0)
QObject::moveToThread: Current thread (0x104a02e0) is not the object's thread (0x1ade640).
Cannot move to target thread (0x104a02e0)


Spyder (Python 3.11)
Peson 15
Console 36/A
Cannot move to target thread (0x104a02e0)
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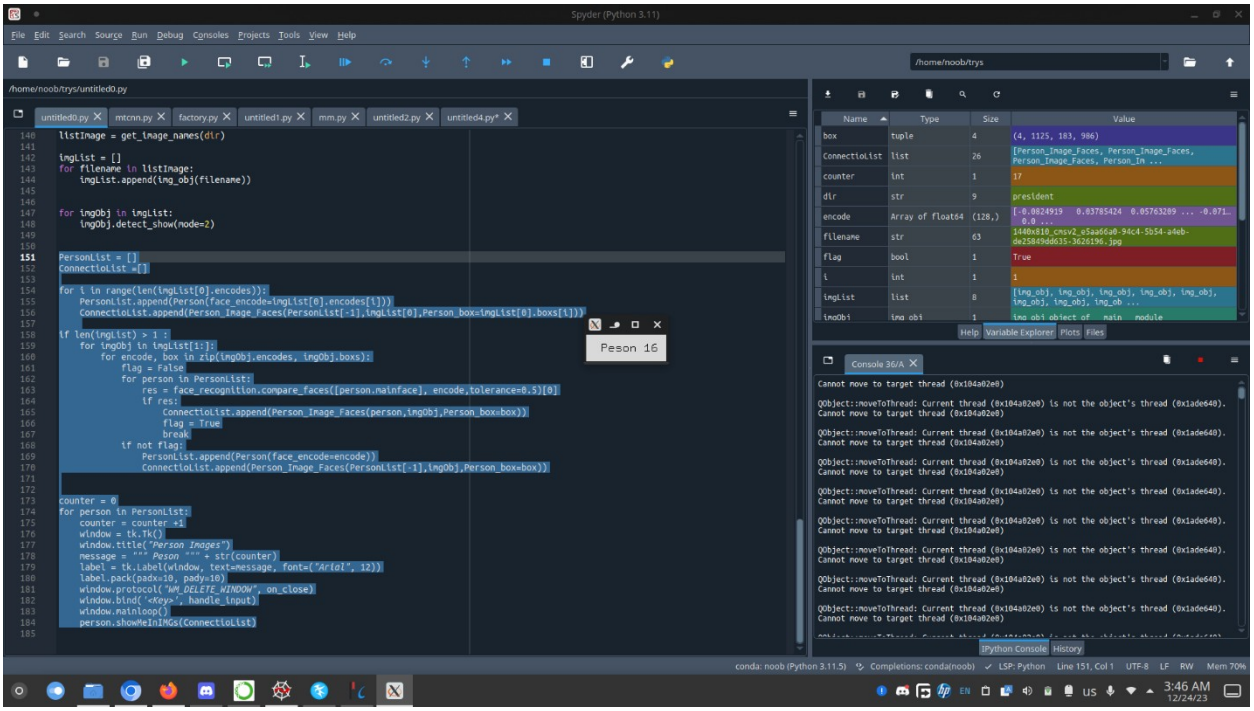
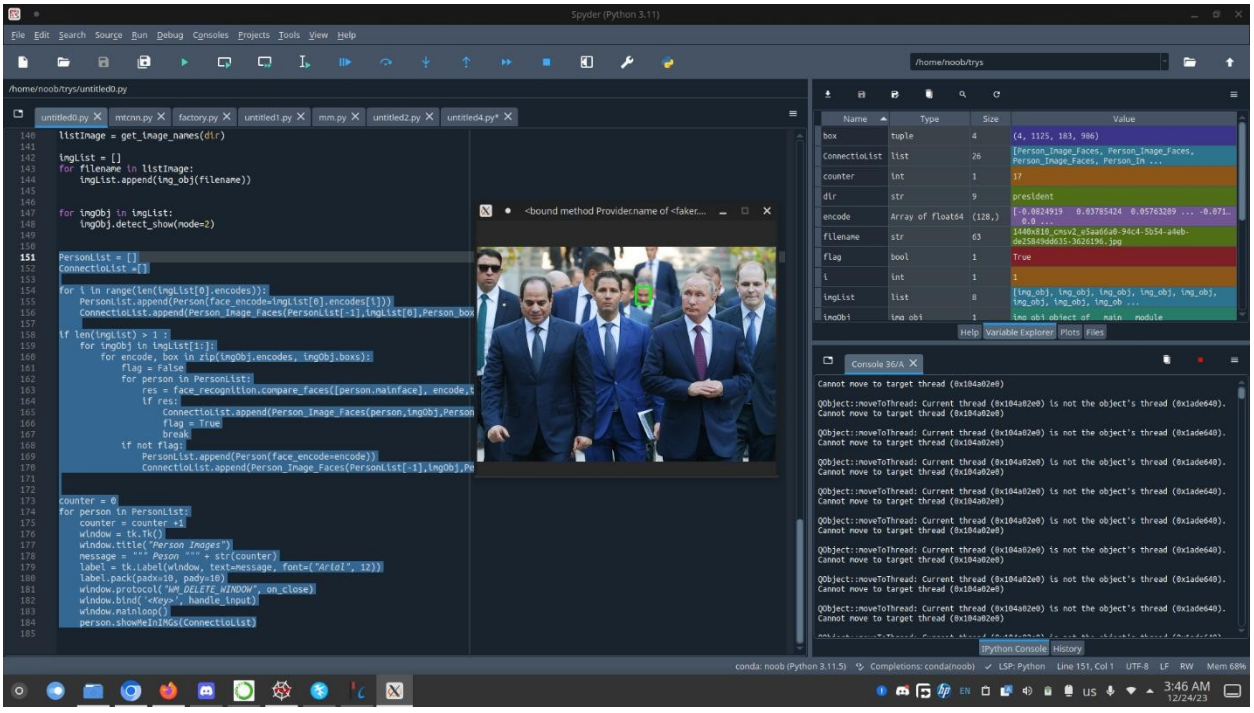
16. Person 16:


Spyder (Python 3.11)
Peson 16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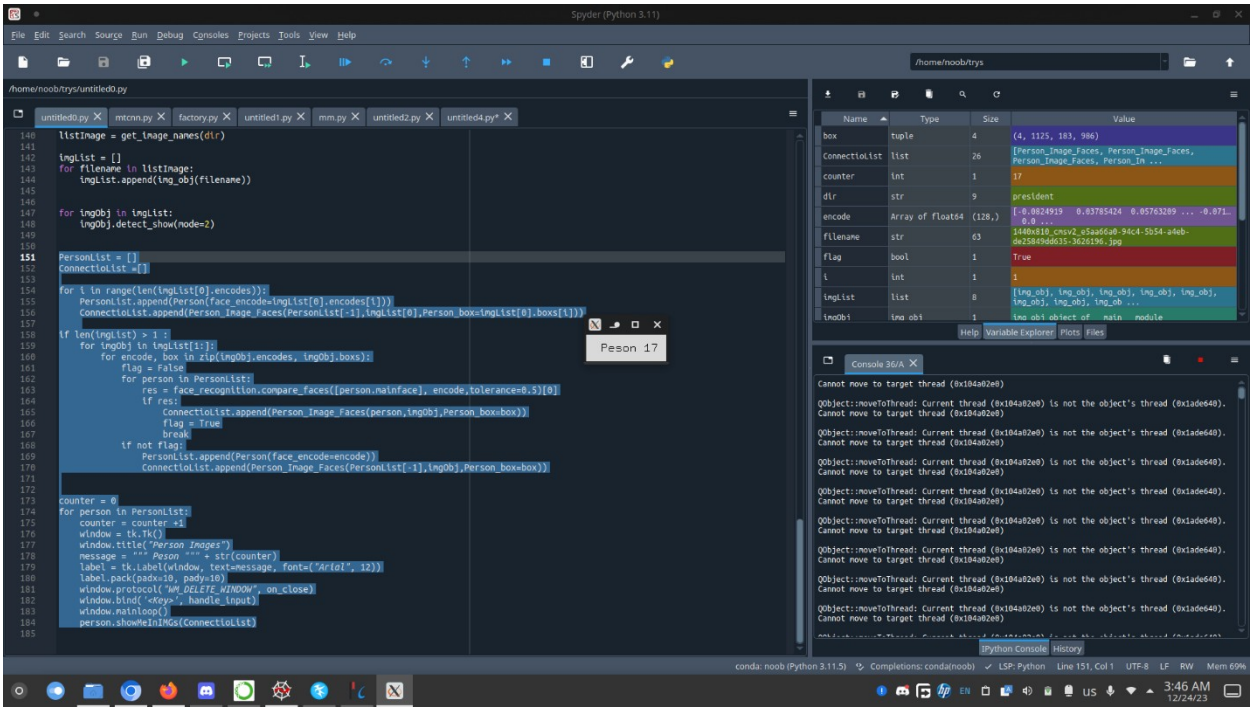
17. Person 17: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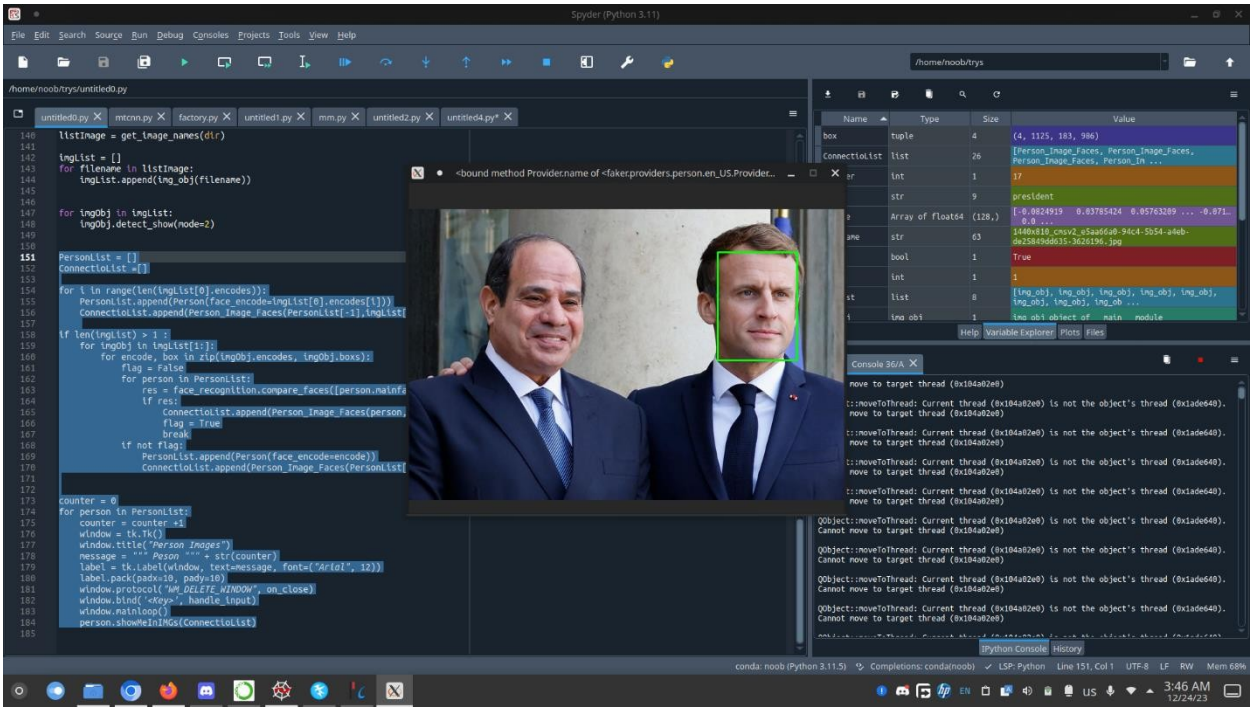
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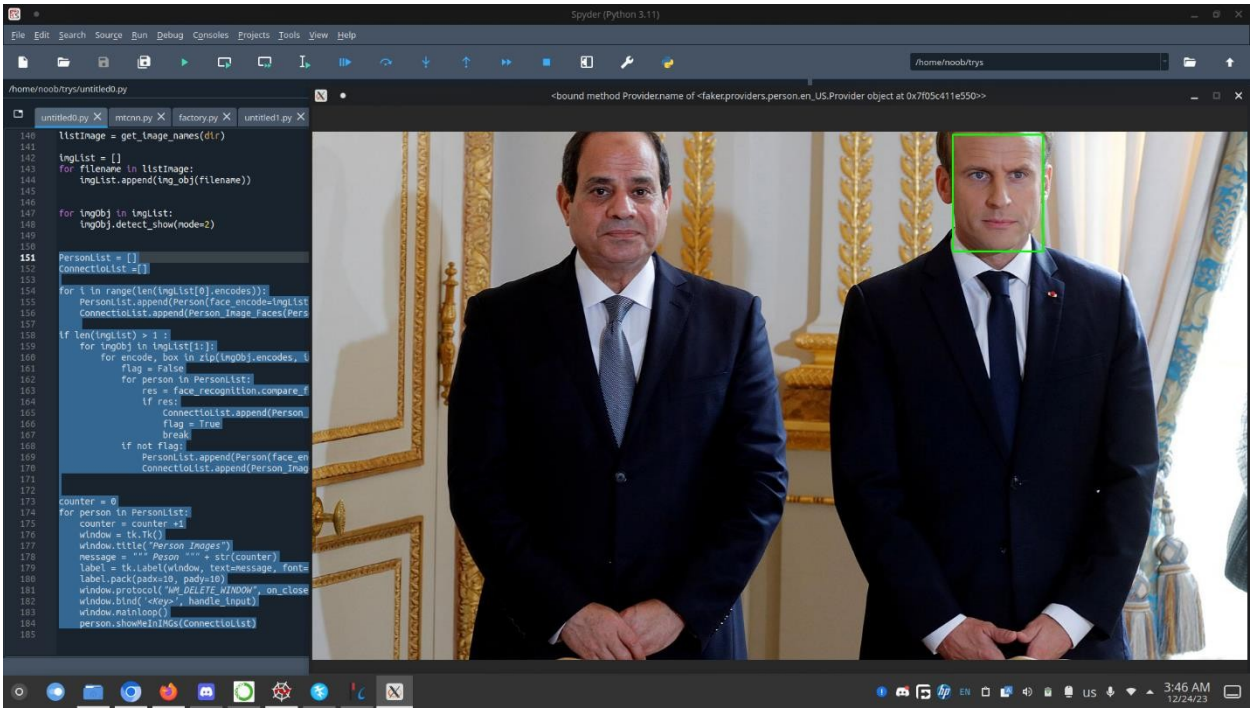
Spyder (Python 3.11)
File Edit Search Source Run Debug Consoles Projects Tools View Help
/home/noob/trys
/home/noob/trys/untitled0.py
untitled0.py
mtcnn.py
factory.py
untitled1.py
<bound method Provider.name of <faker.providers.person.en_US.Provider object at 0x7f05c411e550>>
listImage = get_image_names(dir)
imgList = []
for filename in listImage:
imgList.append(img_obj(filename))
for imgObj in imgList:
imgObj.detect_show(mode=2)
PersonList = []
ConnectioList =[]
for i in range(len(imgList[0].encodes)):
PersonList.append(Person(face_encode=imgList
ConnectioList.append(Person_Image_Faces(Pers
if len(imgList) > 1 :
for imgObj in imgList[1:]:
for encode, box in zip(imgObj.encodes, i
flag = False
for person in PersonList:
res = face_recognition.compare_f
if res:
ConnectioList.append(Person_
flag = True
break
if not flag:
PersonList.append(Person(face_en
ConnectioList.append(Person_Imag
counter = 0
for person in PersonList:
counter = counter +1
window = tk.Tk()
window.title("Person Images")
message = "Person " + str(counter)
label = tk.Label(window, text=message, font=
label.pack(padx=10, pady=10)
window.protocol("WM_DELETE_WINDOW", on_close
window.bind('<Key>', handle_input)
window.mainloop()
person.showHeInIMGs(ConnectioList)
3:46 AM
12/24/23

Discussion:

The presented program exhibits a sophisticated approach to the task of consolidating pictures of individuals across multiple images, demonstrating a seamless integration of advanced algorithms and libraries. The use of the MTCNN (Multi-task Cascaded Convolutional Networks) algorithm for face detection introduces a reliable mechanism for identifying faces within images, while the subsequent conversion of face box formats ensures compatibility with the face_recognition library. Leveraging face_recognition with the HOG (Histogram of Oriented Gradients) algorithm and additional techniques like num_jitters enable the extraction of intricate facial features, contributing to accurate face recognition. One notable aspect of the algorithm is its systematic organization, starting with the reading of image paths, processing of images, and the establishment of a Person List and Connection List. The initialization of persons from the first image and the creation of connections between them provide a solid foundation for subsequent iterations. The iterative process of analyzing each image and checking for existing persons based on encoding differences ensures a comprehensive and dynamic approach to handling varied datasets. The choice of coding practices, incorporating a suite of libraries such as cv2, copy, Faker, tkinter, os, mtcnn, face_recognition, dlib, and CUDA drivers, reflects a commitment to efficiency and performance. The inclusion of CUDA drivers for GPU acceleration underscores the program's scalability, allowing for faster processing and handling of larger datasets. Despite the absence of training data, the program showcases its adaptability by relying on the pre-trained MTCNN model. This decision simplifies the user experience, as users can seamlessly push pictures into the application without the need for additional training steps.In the testing phase, the program has demonstrated success in critical functionalities, including reading input images, classifying faces, and recognizing individuals. The robustness of the algorithm, combined with effective coding practices and library utilization, positions this application as a valuable tool in scenarios where efficient face recognition and picture organization are paramount, such as smartphone photo studios or similar environments. Overall, the discussion highlights the program's strengths in algorithmic design, coding practices, and real-world applicability.

Conclusion

In conclusion, the developed program is a robust solution for consolidating pictures of individuals across multiple images, serving as an asset in smartphone photo studios or settings requiring efficient face recognition and categorization. The algorithm systematically reads image paths, processes images using the MTCNN face detection algorithm with specified confidence thresholds and converts face box formats for compatibility with the face_recognition library. Utilizing face_recognition with HOG and num_jitters, the program calculates face encodings to extract detailed features. It establishes a Person List and Connection List, initializing persons from the first image and creating connections between them. Subsequent images are then analyzed, checking for existing people in the Person List based on encoding differences, and creating new persons as needed. The program leverages libraries such as cv2, copy, Faker, tkinter, os, mtcnn, face_recognition, dlib, and CUDA drivers for GPU acceleration. Notably, the application excels in testing, successfully reading input images, classifying faces, and recognizing individuals, showcasing its efficacy in seamlessly organizing and consolidating pictures through the adept integration of advanced algorithms and libraries.

Reference

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