7.2 Google Colab - Algoritmos de extracción de Caraterísticas - Harris Detector

Equipo 10:

Carlos Roberto Torres Ferguson - A01215432

Andrea Carolina Treviño Garza - A01034993

Julio Adrián Quintana Gracia - A01793661

Pablo Alejandro Colunga Vázquez - A01793671

7. Harris Edge & Corner Detection

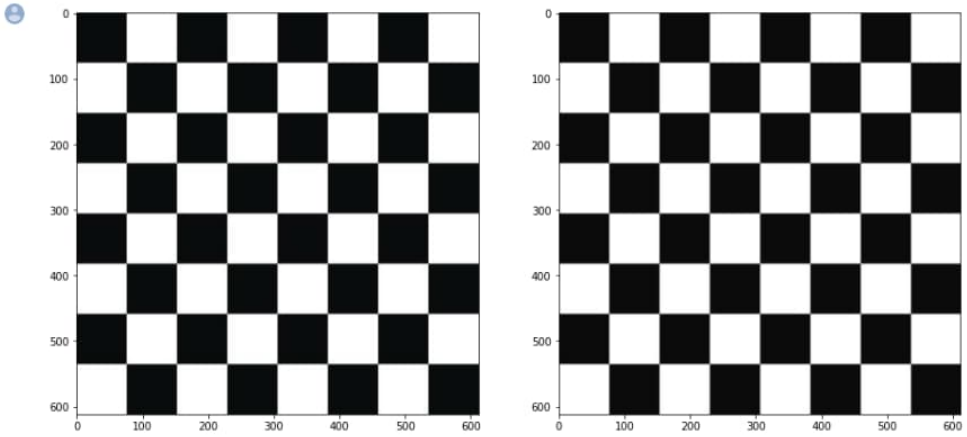
Table of Contents

Importing Libraries

```
[ ]  import cv2
     import matplotlib.pyplot as plt
     from scipy import signal as sig
     import numpy as np
     from scipy.ndimage.filters import convolve
```

1. Color to Grayscale

```
img = cv2.imread('/content/chessboard.jpg')
img_color = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
img_gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_color)
plt.subplot(1, 2, 2)
plt.imshow(img_gray, cmap="gray")
plt.show()
```



2. Spatial derivative calculation

```
[ ]  def gradient_x(imggray):
         ##Sobel operator kernels.
         kernel_x = np.array([[-1, 0, 1],[-2, 0, 2],[-1, 0, 1]])
         return sig.convolve2d(imggray, kernel_x, mode='same')

     def gradient_y(imggray):
         kernel_y = np.array([[1, 2, 1], [0, 0, 0], [-1, -2, -1]])
         return sig.convolve2d(imggray, kernel_y, mode='same')

     I_x = gradient_x(img_gray)
     I_y = gradient_y(img_gray)
```

3. Structure tensor setup

```
[ ]  def gaussian_kernel(size, sigma=1):
         size = int(size) // 2
         x, y = np.mgrid[-size:size+1, -size:size+1]
         normal = 1 / (2.0 * np.pi * sigma**2)
         g =  np.exp(-((x**2 + y**2) / (2.0*sigma**2))) * normal
         return g


     Ixx = convolve(I_x**2, gaussian_kernel(3, 1))
     Ixy = convolve(I_y*I_x, gaussian_kernel(3, 1))
     Iyy = convolve(I_y**2, gaussian_kernel(3, 1))
```

4. Harris response calculation

```
[ ] k = 0.05

    # determinant
    detA = Ixx * Iyy - Ixy ** 2

    # trace
    traceA = Ixx + Iyy

    harris_response = detA - k * traceA ** 2
```

```
[ ] img_gray.shape
```

```
    (612, 612)
```

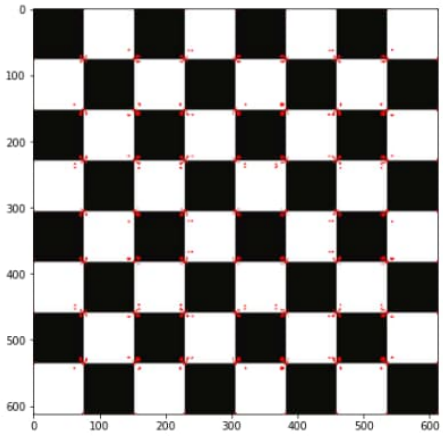
```
[ ] window_size = 3
    offset = window_size//2
    width, height = img_gray.shape

    for y in range(offset, height-offset):
        for x in range(offset, width-offset):
            Sxx = np.sum(Ixx[y-offset:y+1+offset, x-offset:x+1+offset])
            Syy = np.sum(Iyy[y-offset:y+1+offset, x-offset:x+1+offset])
            Sxy = np.sum(Ixy[y-offset:y+1+offset, x-offset:x+1+offset])
```

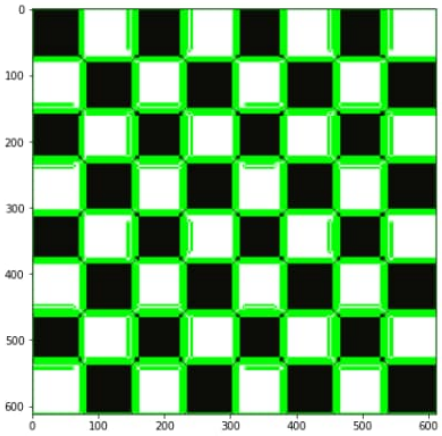
```
[ ] #Find determinant and trace, use to get corner response
    det = (Sxx * Syy) - (Sxy**2)
    trace = Sxx + Syy
    r = det - k*(trace**2)
```

5. Find edges and corners using R

```
[ ] img_copy_for_corners = np.copy(img)
    img_copy_for_edges = np.copy(img)

    for rowindex, response in enumerate(harris_response):
        for colindex, r in enumerate(response):
            if r > 0:
                # this is a corner
                img_copy_for_corners[rowindex, colindex] = [255,0,0]
            elif r < 0:
                # this is an edge
                img_copy_for_edges[rowindex, colindex] = [0,255,0]
```

```
[ ] plt.figure(figsize=(15, 8))
    plt.subplot(1, 2, 1)
    plt.imshow(img_copy_for_corners, cmap="gray")
    plt.subplot(1, 2, 2)
    plt.imshow(img_copy_for_edges, cmap="gray")
    plt.show()
```



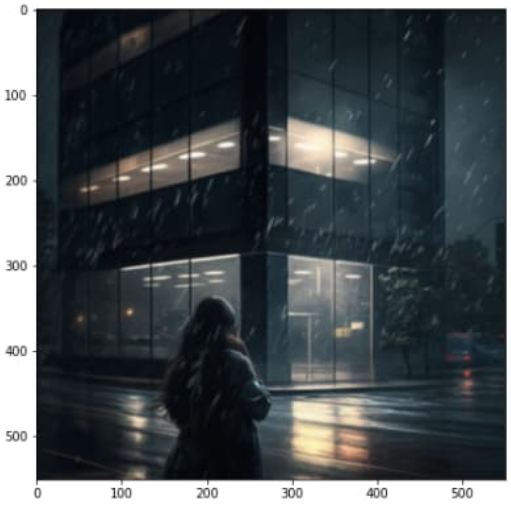
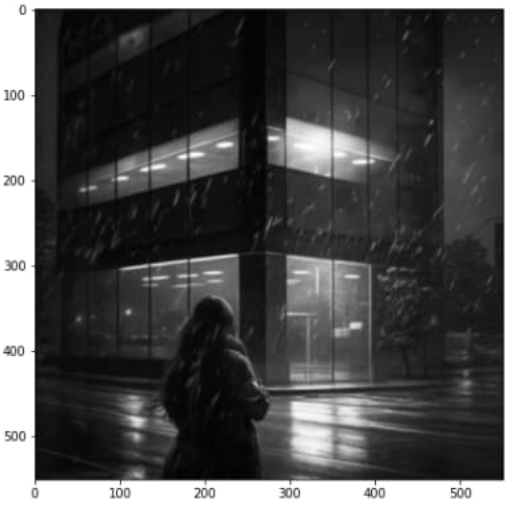


Ejercicio

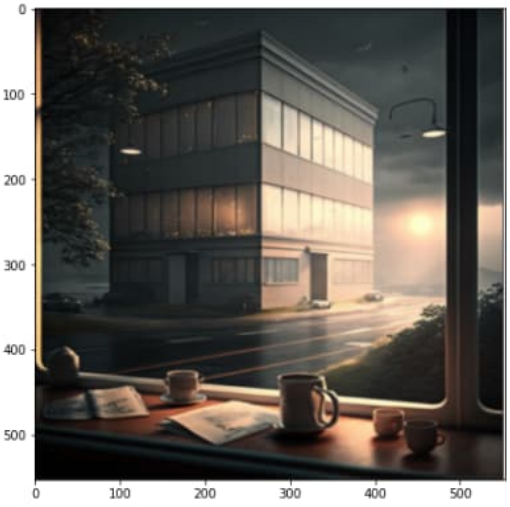
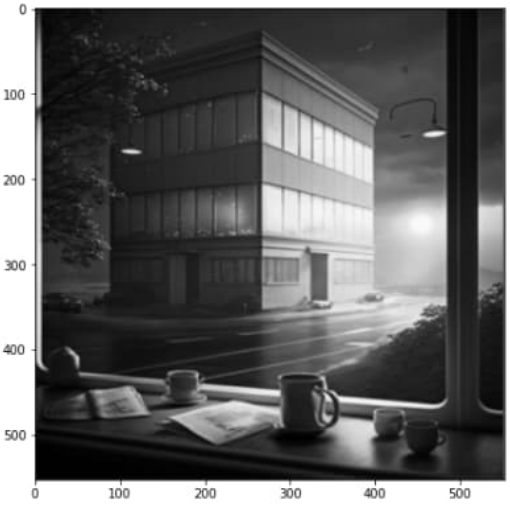
```
[ ]  # img#1
     img_1 = cv2.imread('/content/cv1.png')
     img_color_1 = cv2.cvtColor(img_1, cv2.COLOR_BGR2RGB)
     img_gray_1 = cv2.cvtColor(img_1, cv2.COLOR_BGR2GRAY)

     plt.figure(figsize=(15, 8))
     plt.subplot(1, 2, 1)
     plt.imshow(img_color_1)
     plt.subplot(1, 2, 2)
     plt.imshow(img_gray_1, cmap="gray")

     # img#2
     img_2 = cv2.imread('/content/cv2.png')
     img_color_2 = cv2.cvtColor(img_2, cv2.COLOR_BGR2RGB)
     img_gray_2 = cv2.cvtColor(img_2, cv2.COLOR_BGR2GRAY)

     plt.figure(figsize=(15, 8))
     plt.subplot(1, 2, 1)
     plt.imshow(img_color_2)
     plt.subplot(1, 2, 2)
     plt.imshow(img_gray_2, cmap="gray")

     # img#3
     img_3 = cv2.imread('/content/cv3.png')
     img_color_3 = cv2.cvtColor(img_3, cv2.COLOR_BGR2RGB)
     img_gray_3 = cv2.cvtColor(img_3, cv2.COLOR_BGR2GRAY)

     plt.figure(figsize=(15, 8))
     plt.subplot(1, 2, 1)
     plt.imshow(img_color_3)
     plt.subplot(1, 2, 2)
     plt.imshow(img_gray_3, cmap="gray")
```

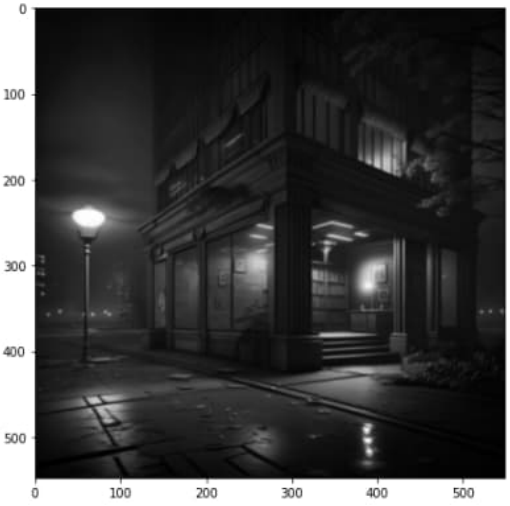
```
# img#4
img_4 = cv2.imread('/content/cv4.png')
img_color_4 = cv2.cvtColor(img_4, cv2.COLOR_BGR2RGB)
img_gray_4 = cv2.cvtColor(img_4, cv2.COLOR_BGR2GRAY)

plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_color_4)
plt.subplot(1, 2, 2)
plt.imshow(img_gray_4, cmap="gray")

# img#5
img_5 = cv2.imread('/content/cv5.png')
img_color_5 = cv2.cvtColor(img_5, cv2.COLOR_BGR2RGB)
img_gray_5 = cv2.cvtColor(img_5, cv2.COLOR_BGR2GRAY)

plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_color_5)
plt.subplot(1, 2, 2)
plt.imshow(img_gray_5, cmap="gray")

# img#6
img_6 = cv2.imread('/content/cv6.png')
img_color_6 = cv2.cvtColor(img_6, cv2.COLOR_BGR2RGB)
img_gray_6 = cv2.cvtColor(img_6, cv2.COLOR_BGR2GRAY)

plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_color_6)
plt.subplot(1, 2, 2)
plt.imshow(img_gray_6, cmap="gray")
```

```
<matplotlib.image.AxesImage at 0x7f40de3eabe0>
```

[ ]

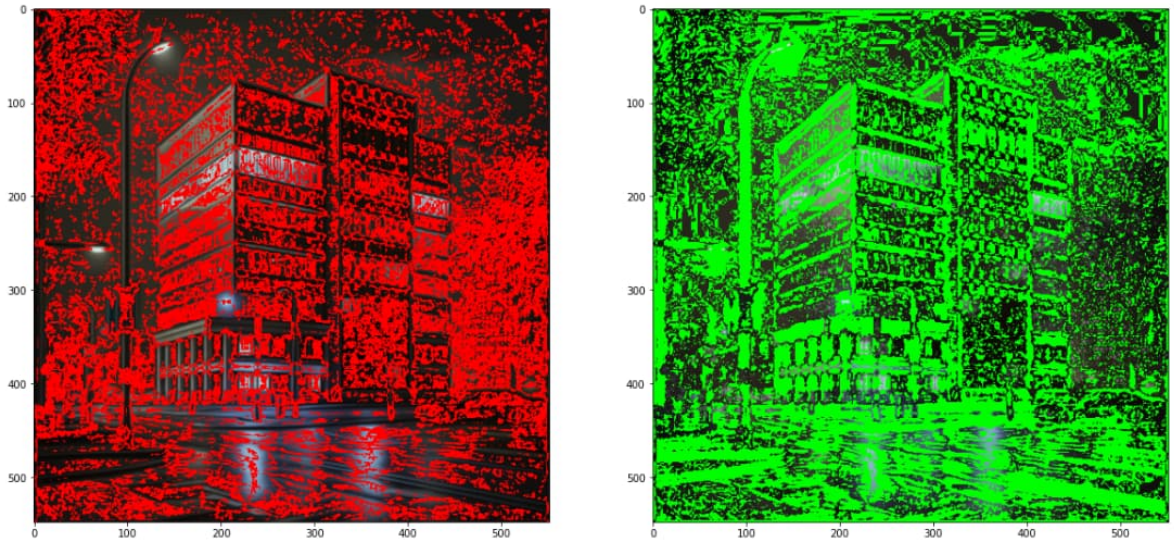



```
def gradient_x(imggray):
    ##Sobel operator kernels.
    kernel_x = np.array([[-1, 0, 1],[-2, 0, 2],[-1, 0, 1]])
    return sig.convolve2d(imggray, kernel_x, mode='same')

def gradient_y(imggray):
    kernel_y = np.array([[1, 2, 1], [0, 0, 0], [-1, -2, -1]])
    return sig.convolve2d(imggray, kernel_y, mode='same')

def gaussian_kernel(size, sigma=1):
    size = int(size) // 2
    x, y = np.mgrid[-size:size+1, -size:size+1]
    normal = 1 / (2.0 * np.pi * sigma**2)
    g =  np.exp(-((x**2 + y**2) / (2.0*sigma**2))) * normal
    return g
```

```
[ ]  def harris_edge_corner_detection(img_gray, img):
       # Spatial derivative calculation
       I_x = gradient_x(img_gray)
       I_y = gradient_y(img_gray)

       # Structure tensor setup
       Ixx = convolve(I_x**2, gaussian_kernel(3, 1))
       Ixy = convolve(I_y*I_x, gaussian_kernel(3, 1))
       Iyy = convolve(I_y**2, gaussian_kernel(3, 1))

       # Harris response calculation
       k = 0.05

       # determinant
       detA = Ixx * Iyy - Ixy ** 2

       # trace
       traceA = Ixx + Iyy

       harris_response = detA - k * traceA ** 2


       window_size = 3
       offset = window_size//2
       width, height = img_gray.shape
```

```
       for y in range(offset, height-offset):
           for x in range(offset, width-offset):
               Sxx = np.sum(Ixx[y-offset:y+1+offset, x-offset:x+1+offset])
               Syy = np.sum(Iyy[y-offset:y+1+offset, x-offset:x+1+offset])
               Sxy = np.sum(Ixy[y-offset:y+1+offset, x-offset:x+1+offset])

       #Find determinant and trace, use to get corner response
       det = (Sxx * Syy) - (Sxy**2)
       trace = Sxx + Syy
       r = det - k*(trace**2)

       # Finding corners and edgers using R
       img_copy_for_corners = np.copy(img)
       img_copy_for_edges = np.copy(img)

       for rowindex, response in enumerate(harris_response):
           for colindex, r in enumerate(response):
               if r > 0:
                   # this is a corner
                   img_copy_for_corners[rowindex, colindex] = [255,0,0]
               elif r < 0:
                   # this is an edge
                   img_copy_for_edges[rowindex, colindex] = [0,255,0]


       plt.figure(figsize=(20, 10))
       plt.subplot(1, 2, 1)
       plt.imshow(img_copy_for_corners, cmap="gray")
       plt.subplot(1, 2, 2)
       plt.imshow(img_copy_for_edges, cmap="gray")
```

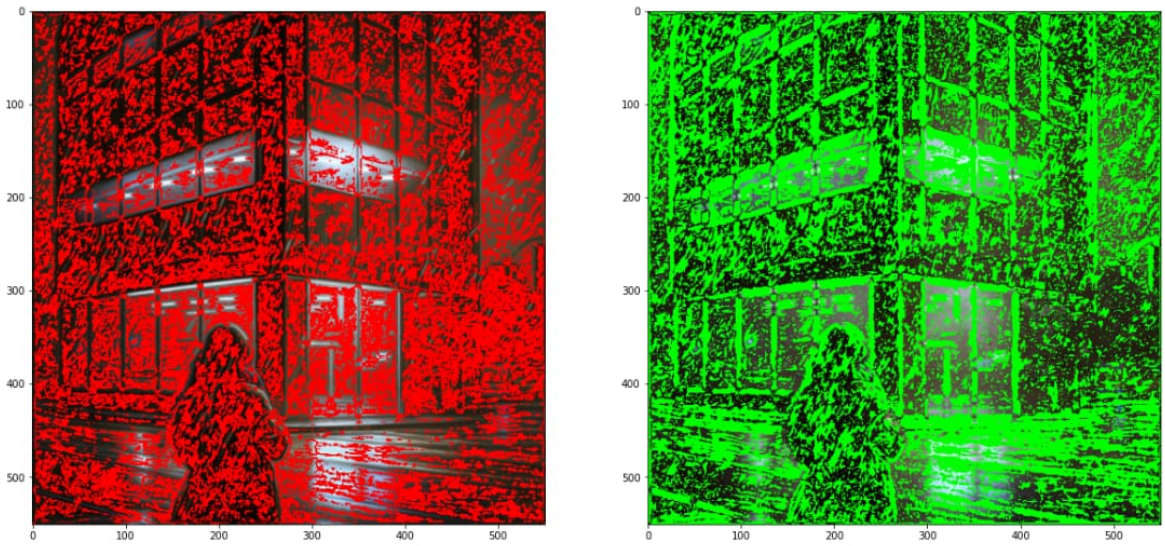
```
[ ] harris_edge_corner_detection(img_gray_1, img_1)
```



Img#1 - Edificio de noche

- **Esquinas (rojo):** se observa que algoritmo de Harris detecta muchas más esquinas de la esperadas. Por ejemplo en las nubes, que tienes contornos muy suaves y no tan distinguibles o en la luces reflejadas en el suelo. Mientras en el edificio central de la foto con sus ventanas sí se detectaron esquinas relevantes. Pero nuevamente detectó más esquinas de las esperadas en secciones que se perciben casi lisas entre las ventanas del edificio principal.

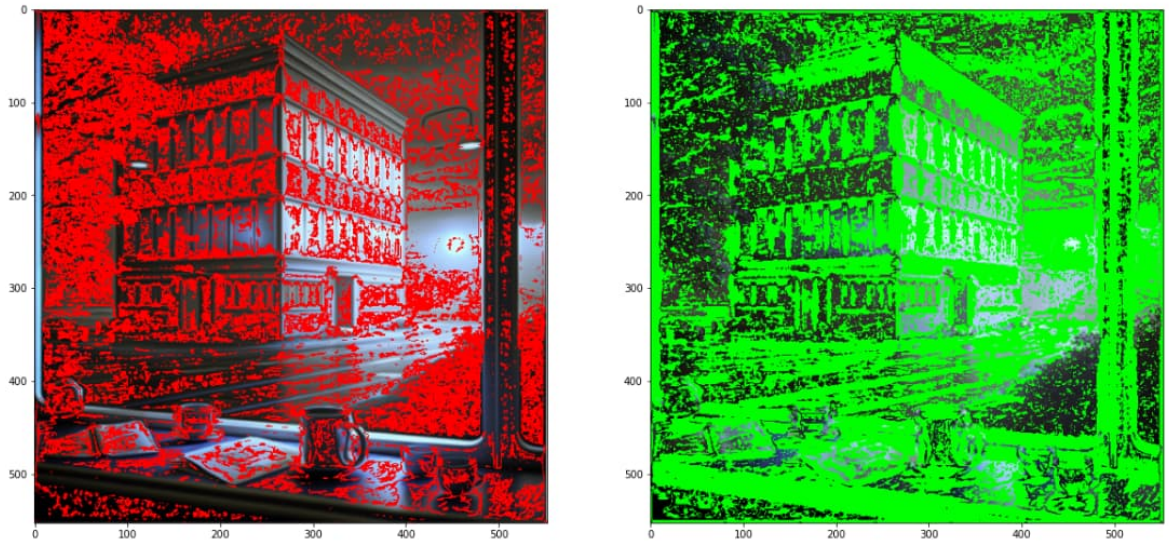
```
[ ] harris_edge_corner_detection(img_gray_2, img_2)
```



Img#2 - Edificio de noche con lluvia.

- **Esquinas (rojo):** en esta imagen imagen se observa claramente el contraste, donde practicamente todo lo que que el algoritmo no está detectando como esquina lo está clasificando con borde. Bordes de ventanas, puertas y edificios se aprecian con facilidad. Pero secciones que se perciben lisas y sin bordes, las marca en rojo el algoritmo.
- **Bordes (verde):** para los bordes se identifican las diagonales de la lluvia (característca de interés en la imagen para comparación), las líneas de las calles, puertas y ventanas de edificio.

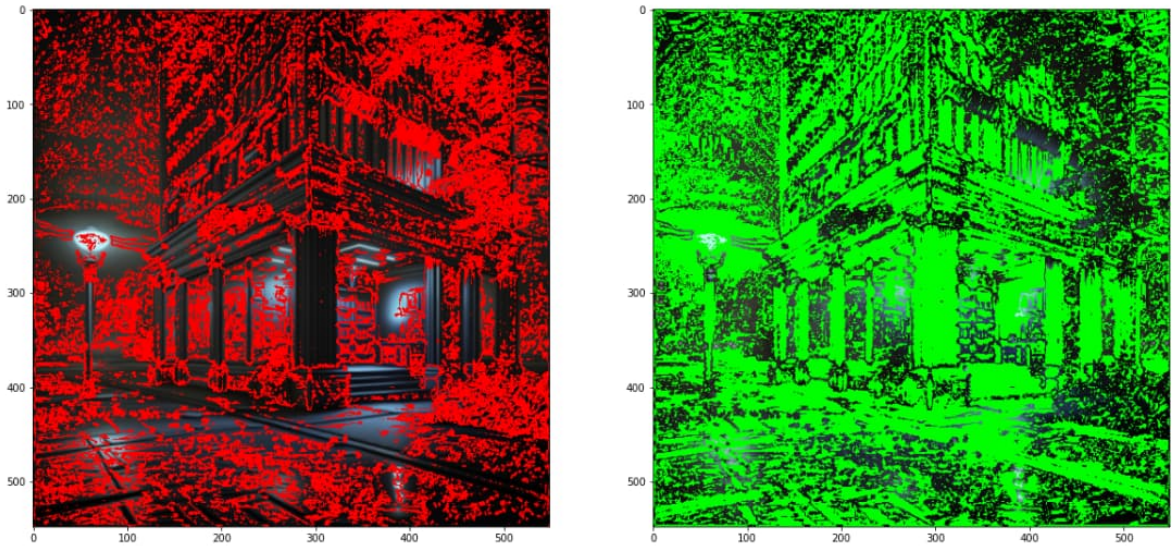
```
[ ]  harris_edge_corner_detection(img_gray_3, img_3)
```



Img#3 - Edificio al amanecer.

- **Esquinas (rojo):** en las secciones de la imagen donde el contraste entre la iluminación es donde se perciben mejores resultados en la identidicación de bordes, como en el marco de la ventana que enmarca al edificio.
- **Bordes (verde):** a pesar de tener mejor iluminación la imagen, no detecta las líneas principalmente de manera continua. Como se espera en contornos de edificio.

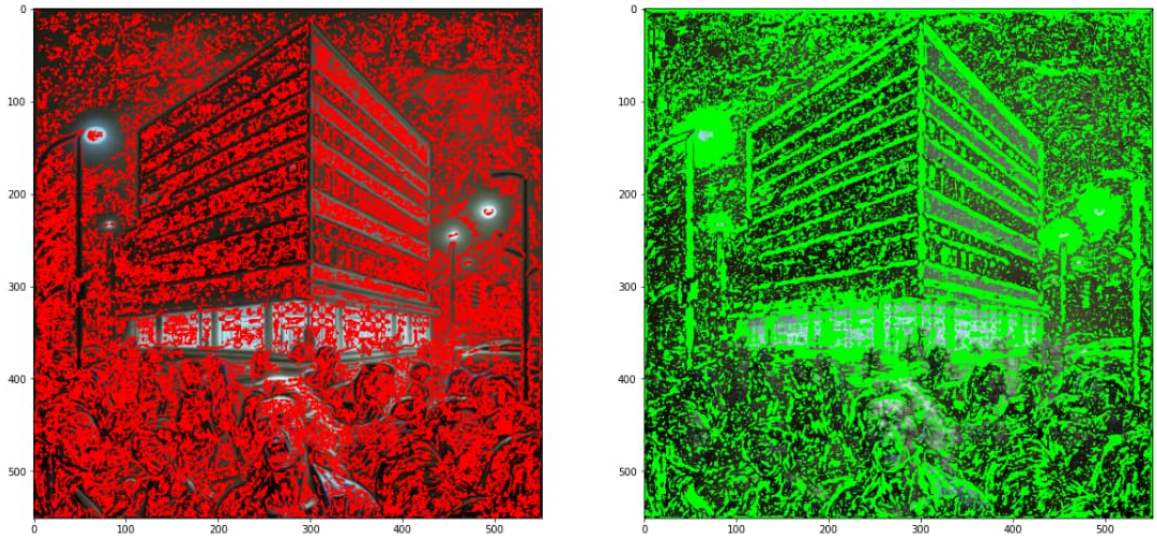
```
harris_edge_corner_detection(img_gray_4, img_4)
```



Img#4 - Edificio de noche con mejor ilumnación al interior.

- **Esquinas (rojo):** se observa que hay una mejor identificación de bordes en el interior de l edificio que presenta mayores contrastes entre colores.
- **Bordes (verde):** igualmente se ve saturada la imagen de líneas y no se refleja la continuidad en las líneas rectas del edificio y las calles.

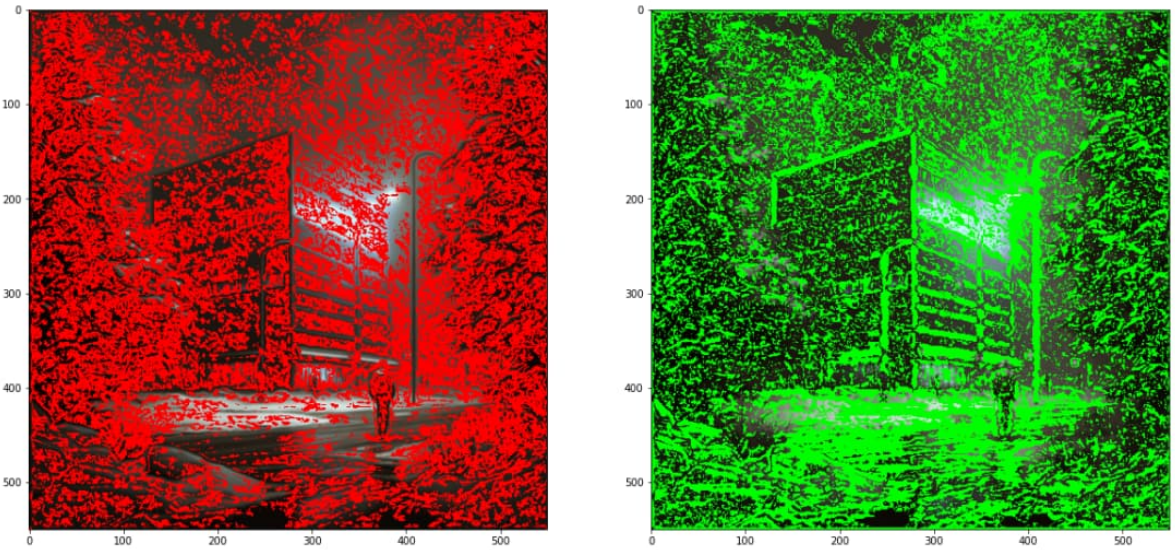
```
[ ] harris_edge_corner_detection(img_gray_5, img_5)
```



Img#5 - Edificio de noche con zombies al frente.

- **Esquinas (rojo):** se perciben buenos resultados en las esquinas del edificio y en general resultados similares al estar en un iluminación nocturna. En líneas curvas, como rostros de zombies, se ven muchos bordes rojos que se pierden entre sí.
- **Bordes (verde):** nuevamente la imagen se ve llena de líneas y solo se observan resultados claros en los bordes del edificio y las lámparas de luz de la calle.

```
[ ] harris_edge_corner_detection(img_gray_6, img_6)
```



Img#5 - Edificio de noche con clima nevado.

- **Esquinas (rojo):** se observan peores resultados en la detección de los bordes del edificio, pues el clima nevado hace que se "suavice" la imagen y haya mucho menor contraste de colores.
- **Bordes (verde):** pasa lo mismo con las líneas, menos perceptibles en clima nevado y únicamente las lámparas de luz arrojan mejor identificación de líneas.

CONCLUSIÓN FINAL:

- En general observamos que cuando tienen mucho nivel de detalle las imágenes, es decir, con más profundidades, variaciones de colores y tonalidades, el algoritmo identifica más bordes y esquinas falsos y en mayor cantidad de las realmente se esperan. La recomendación sería utilizar fotos con menor nivel de detalle y menos cambios en luces/tonalidades para observar un mejor rendimiento en el algoritmo, como ocurre con la imagen del tablero de ajedrez. O hacer algún preprocesamiento en la imagen que ayude a reducir el nivel de detalle, utilizando por ejemplo un algoritmo de clustering como K-mean que reduzca la cantidad total de colores.

Referencias:

- Agrawal, S. (2021, 27 diciembre). Image Segmentation using K-Means Clustering - The Startup. Medium. https://medium.com/swlh/image-segmentation-using-k-means-clustering-46a60488ae71

7.2 Google Colab - Algoritmos de extracción de Caraterísticas - Matching

Equipo 10:

Carlos Roberto Torres Ferguson - A01215432

Andrea Carolina Treviño Garza - A01034993

Julio Adrián Quintana Gracia - A01793661

Pablo Alejandro Colunga Vázquez - A01793671

9. Image Matching

Table of Contents

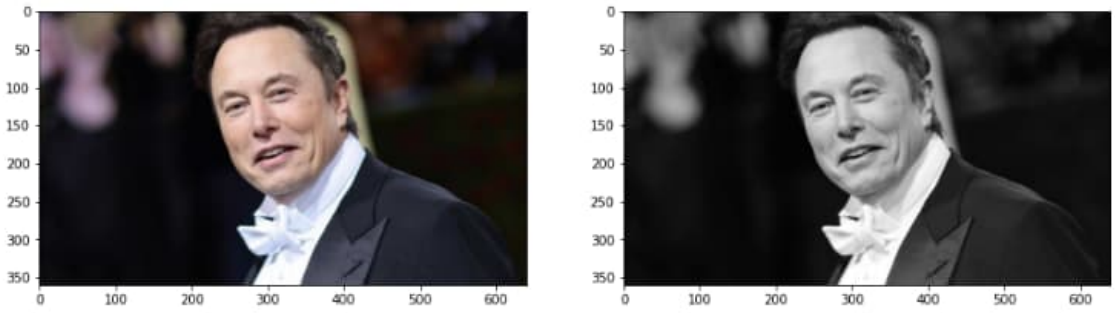
Importing Libraries

```
[1] import cv2
    import matplotlib.pyplot as plt
    import numpy as np
```

ORB (Oriented FAST and Rotated BRIEF)

- Developed at OpenCV labs by Ethan Rublee, Vincent Rabaud, Kurt Konolige, and Gary R. Bradski in 2011
- Efficient and viable alternative to SIFT and SURF (patented algorithms)
- ORB is free to use
- Feature detection
- ORB builds on FAST keypoint detector + BRIEF descriptor

```
[ ]  #reading image
     img = cv2.imread('/content/elon_1.jpg')
     img_color = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
     img_gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

     plt.figure(figsize=(15, 8))
     plt.subplot(1, 2, 1)
     plt.imshow(img_color)
     plt.subplot(1, 2, 2)
     plt.imshow(img_gray, cmap="gray")
     plt.show()
```

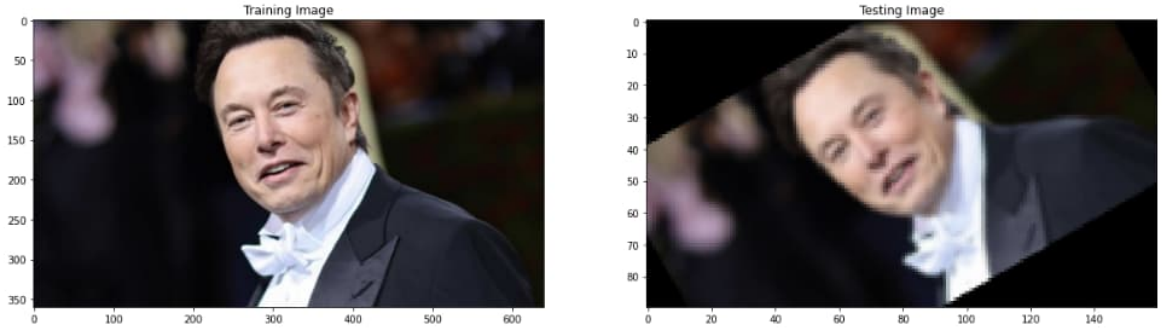


Create test image by adding Scale Invariance and Rotational Invariance

```
[ ]  test_image = cv2.pyrDown(img_color)
     test_image = cv2.pyrDown(test_image)
     num_rows, num_cols = test_image.shape[:2]

     rotation_matrix = cv2.getRotationMatrix2D((num_cols/2, num_rows/2), 30, 1)
     test_image = cv2.warpAffine(test_image, rotation_matrix, (num_cols, num_rows))

     test_gray = cv2.cvtColor(test_image, cv2.COLOR_RGB2GRAY)
```

Display traning image and testing image

```
[ ]  fx, plots = plt.subplots(1, 2, figsize=(20,10))

     plots[0].set_title("Training Image")
     plots[0].imshow(img_color)

     plots[1].set_title("Testing Image")
     plots[1].imshow(test_image)
     plt.show()
```

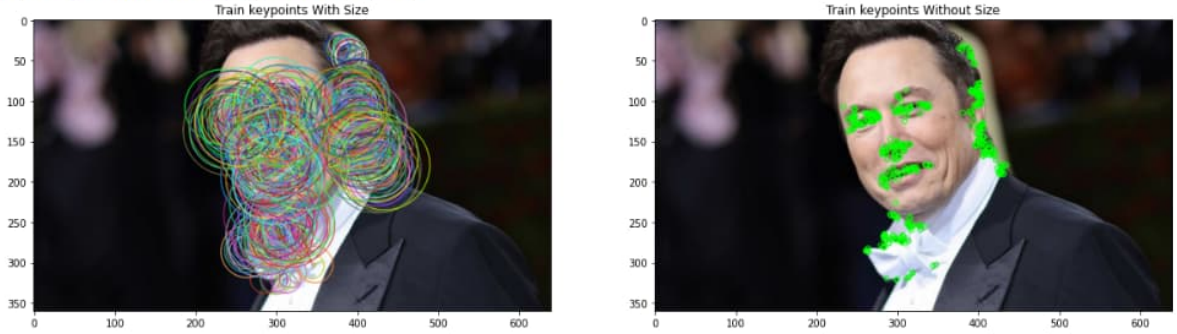


ORB

```
[ ] orb = cv2.ORB_create()
```

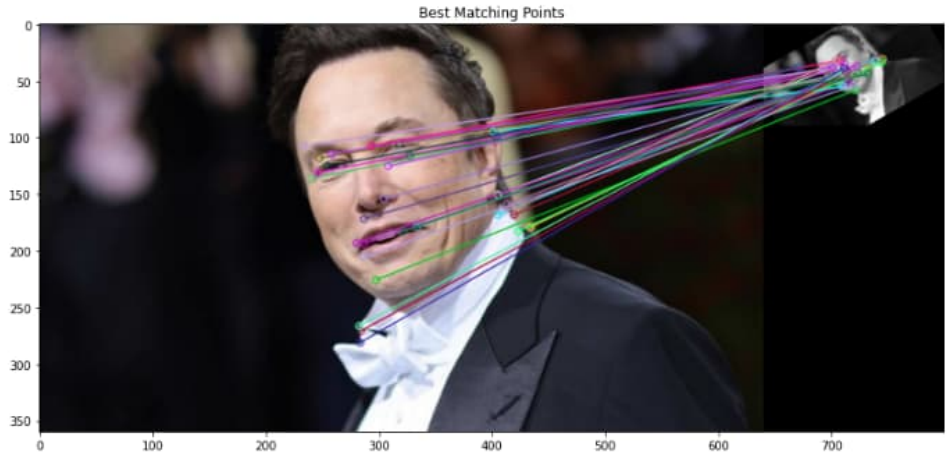
```
[ ] train_keypoints, train_descriptor = orb.detectAndCompute(img_color, None)
    test_keypoints, test_descriptor = orb.detectAndCompute(test_gray, None)

    keypoints_without_size = np.copy(img_color)
    keypoints_with_size = np.copy(img_color)

    cv2.drawKeypoints(img_color, train_keypoints, keypoints_without_size, color = (0, 255, 0))

    cv2.drawKeypoints(img_color, train_keypoints, keypoints_with_size, flags = cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)

    # Display image with and without keypoints size
    fx, plots = plt.subplots(1, 2, figsize=(20,10))

    plots[0].set_title("Train keypoints With Size")
    plots[0].imshow(keypoints_with_size, cmap='gray')

    plots[1].set_title("Train keypoints Without Size")
    plots[1].imshow(keypoints_without_size, cmap='gray')

    # Print the number of keypoints detected in the training image
    print("Number of Keypoints Detected In The Training Image: ", len(train_keypoints))

    # Print the number of keypoints detected in the query image
    print("Number of Keypoints Detected In The Query Image: ", len(test_keypoints))
```

```
Number of Keypoints Detected In The Training Image:  500
Number of Keypoints Detected In The Query Image:  42
```




```
[ ] # Create a Brute Force Matcher object.
    bf = cv2.BFMatcher(cv2.NORM_HAMMING, crossCheck = True)

    # Perform the matching between the ORB descriptors of the training image and the test image
    matches = bf.match(train_descriptor, test_descriptor)

    # The matches with shorter distance are the ones we want.
    matches = sorted(matches, key = lambda x : x.distance)

    result = cv2.drawMatches(img_color, train_keypoints, test_gray, test_keypoints, matches, test_gray, flags = 2)

    # Display the best matching points
    plt.rcParams['figure.figsize'] = [14.0, 7.0]
    plt.title('Best Matching Points')
    plt.imshow(result)
    plt.show()
```

```
# Print total number of matching points between the training and query images
print("\nNumber of Matching Keypoints Between The Training and Query Images: ", len(matches))
```



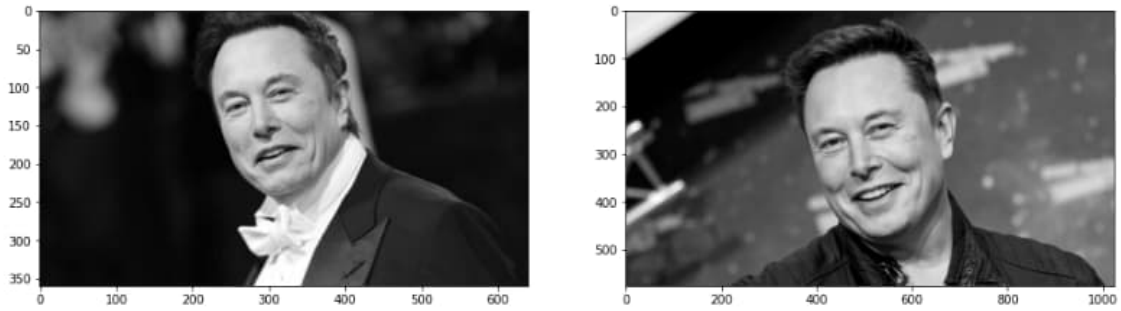

```
Number of Matching Keypoints Between The Training and Query Images:  30
```

SIFT Matching (Scale Invariant Feature Transform)

```
[ ] img1 = cv2.imread('/content/elon_1.jpg')
    gray1 = cv2.cvtColor(img1, cv2.COLOR_BGR2GRAY)

    #keypoints
    sift = cv2.SIFT_create()
    keypoints_1, descriptors_1 = sift.detectAndCompute(img1,None)

    img_1 = cv2.drawKeypoints(gray1,keypoints_1,img1)
    plt.imshow(img_1)
    plt.show()
```

Matching different images

```
[ ]  # read images
     img1 = cv2.imread('/content/elon_1.jpg')
     img2 = cv2.imread('/content/elon_2.png')

     img1 = cv2.cvtColor(img1, cv2.COLOR_BGR2GRAY)
     img2 = cv2.cvtColor(img2, cv2.COLOR_BGR2GRAY)

     figure, ax = plt.subplots(1, 2, figsize=(16, 8))

     ax[0].imshow(img1, cmap='gray')
     ax[1].imshow(img2, cmap='gray')
     plt.show()
```



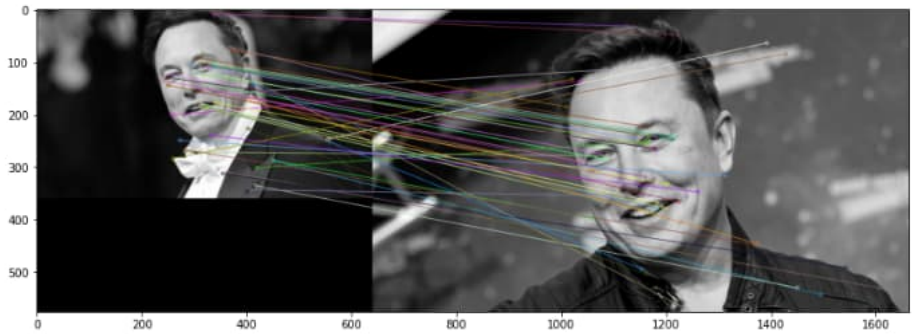
Extracting Keypoints with SIFT

```
[ ]  #sift
     sift = cv2.SIFT_create()

     keypoints_1, descriptors_1 = sift.detectAndCompute(img1,None)
     keypoints_2, descriptors_2 = sift.detectAndCompute(img2,None)

     len(keypoints_1), len(keypoints_2)
```

```
(291, 734)
```

Feature Matching

```
[ ]  #feature matching
     bf = cv2.BFMatcher(cv2.NORM_L1, crossCheck=True)

     matches = bf.match(descriptors_1,descriptors_2)
     matches = sorted(matches, key = lambda x:x.distance)

     img3 = cv2.drawMatches(img1, keypoints_1, img2, keypoints_2, matches[:50], img2, flags=2)
     plt.imshow(img3)
     plt.show()
```

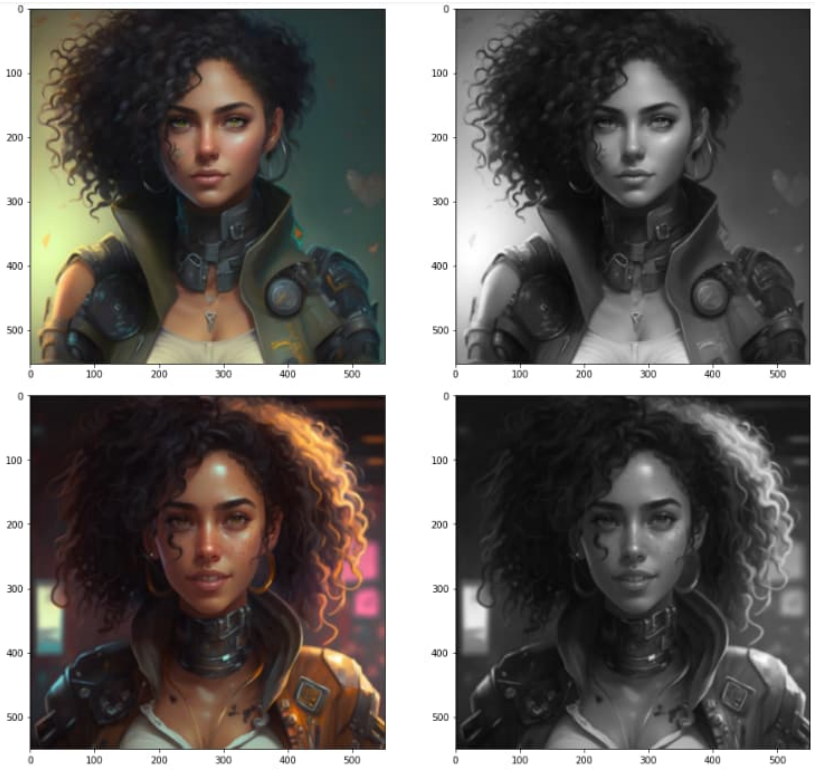


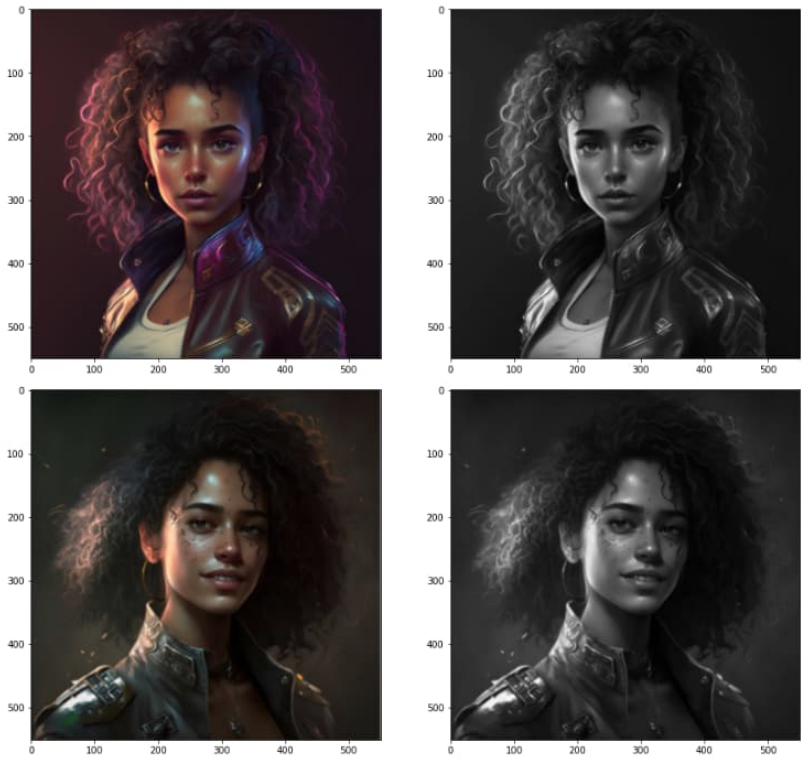
Ejercicio

[2]
```
# img#1
img_1 = cv2.imread('/content/cv2_1.png')
img_color_1 = cv2.cvtColor(img_1, cv2.COLOR_BGR2RGB)
img_gray_1 = cv2.cvtColor(img_1, cv2.COLOR_BGR2GRAY)

plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_color_1)
plt.subplot(1, 2, 2)
plt.imshow(img_gray_1, cmap="gray")

# img#2
img_2 = cv2.imread('/content/cv2_2.png')
img_color_2 = cv2.cvtColor(img_2, cv2.COLOR_BGR2RGB)
img_gray_2 = cv2.cvtColor(img_2, cv2.COLOR_BGR2GRAY)

plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_color_2)
plt.subplot(1, 2, 2)
plt.imshow(img_gray_2, cmap="gray")

# img#3
img_3 = cv2.imread('/content/cv2_3.png')
img_color_3 = cv2.cvtColor(img_3, cv2.COLOR_BGR2RGB)
img_gray_3 = cv2.cvtColor(img_3, cv2.COLOR_BGR2GRAY)

plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_color_3)
plt.subplot(1, 2, 2)
plt.imshow(img_gray_3, cmap="gray")

# img#4
img_4 = cv2.imread('/content/cv2_4.png')
img_color_4 = cv2.cvtColor(img_4, cv2.COLOR_BGR2RGB)
img_gray_4 = cv2.cvtColor(img_4, cv2.COLOR_BGR2GRAY)

plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_color_4)
plt.subplot(1, 2, 2)
plt.imshow(img_gray_4, cmap="gray")
```

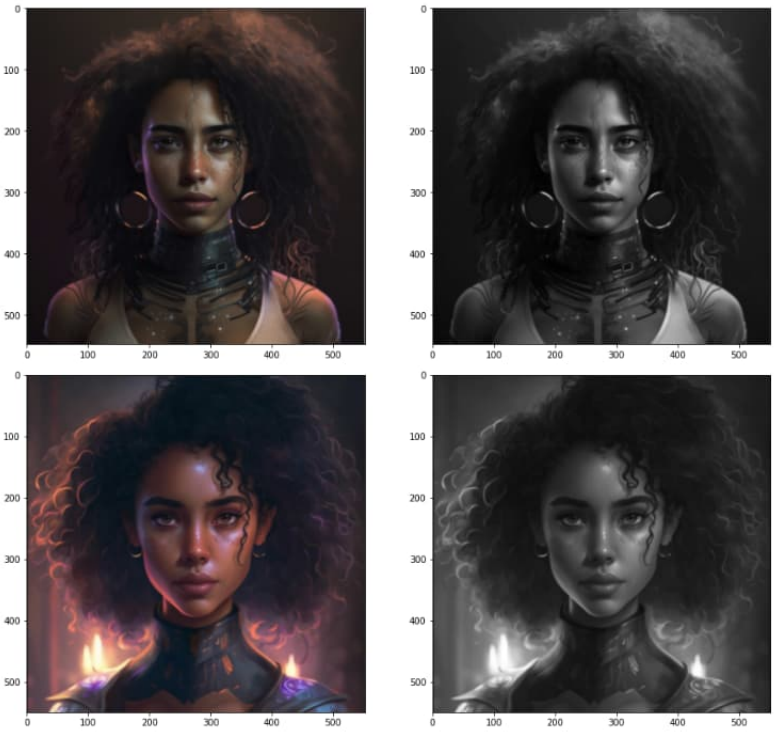
```
# img#5
img_5 = cv2.imread('/content/cv2_5.png')
img_color_5 = cv2.cvtColor(img_5, cv2.COLOR_BGR2RGB)
img_gray_5 = cv2.cvtColor(img_5, cv2.COLOR_BGR2GRAY)

plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_color_5)
plt.subplot(1, 2, 2)
plt.imshow(img_gray_5, cmap="gray")

# img#6
img_6 = cv2.imread('/content/cv2_6.png')
img_color_6 = cv2.cvtColor(img_6, cv2.COLOR_BGR2RGB)
img_gray_6 = cv2.cvtColor(img_6, cv2.COLOR_BGR2GRAY)

plt.figure(figsize=(15, 8))
plt.subplot(1, 2, 1)
plt.imshow(img_color_6)
plt.subplot(1, 2, 2)
plt.imshow(img_gray_6, cmap="gray")
```

[2]
0s





Public

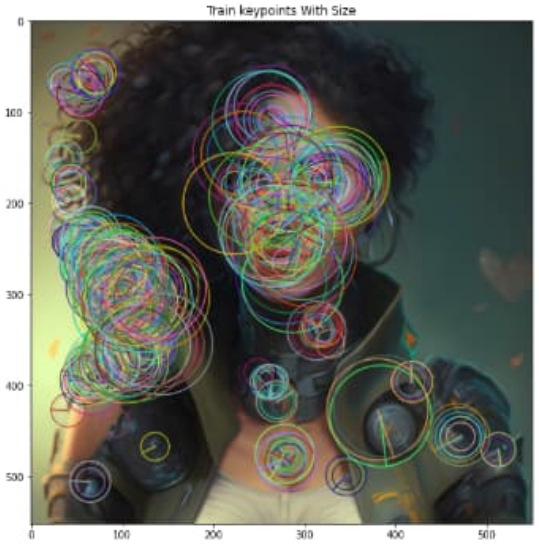


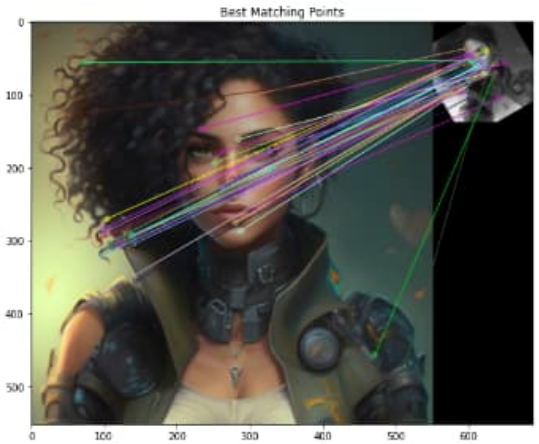
```
[3]  def orb_test(img_color):
       # Create test image by adding Scale Invariance and Rotational Invariance
       test_image = cv2.pyrDown(img_color)
       test_image = cv2.pyrDown(test_image)
       num_rows, num_cols = test_image.shape[:2]

       rotation_matrix = cv2.getRotationMatrix2D((num_cols/2, num_rows/2), 30, 1)
       test_image = cv2.warpAffine(test_image, rotation_matrix, (num_cols, num_rows))

       test_gray = cv2.cvtColor(test_image, cv2.COLOR_RGB2GRAY)

       # Displaying training image and testing image
       fx, plots = plt.subplots(1, 2, figsize=(20,10))

       plots[0].set_title("Training Image")
       plots[0].imshow(img_color)

       plots[1].set_title("Testing Image")
       plots[1].imshow(test_image)

       orb = cv2.ORB_create()

       train_keypoints, train_descriptor = orb.detectAndCompute(img_color, None)
       test_keypoints, test_descriptor = orb.detectAndCompute(test_gray, None)

       keypoints_without_size = np.copy(img_color)
       keypoints_with_size = np.copy(img_color)

       cv2.drawKeypoints(img_color, train_keypoints, keypoints_without_size, color = (0, 255, 0))

       cv2.drawKeypoints(img_color, train_keypoints, keypoints_with_size, flags = cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)

       # Display image with and without keypoints size
       fx, plots = plt.subplots(1, 2, figsize=(20,10))

       plots[0].set_title("Train keypoints With Size")
       plots[0].imshow(keypoints_with_size, cmap='gray')

       plots[1].set_title("Train keypoints Without Size")
       plots[1].imshow(keypoints_without_size, cmap='gray')

       # Print the number of keypoints detected in the training image
       print("Number of Keypoints Detected In The Training Image: ", len(train_keypoints))
```

```
# Print the number of keypoints detected in the query image
print("Number of Keypoints Detected In The Query Image: ", len(test_keypoints))

# Create a Brute Force Matcher object.
bf = cv2.BFMatcher(cv2.NORM_HAMMING, crossCheck = True)

# Perform the matching between the ORB descriptors of the training image and the test image
matches = bf.match(train_descriptor, test_descriptor)

# The matches with shorter distance are the ones we want.
matches = sorted(matches, key = lambda x : x.distance)

result = cv2.drawMatches(img_color, train_keypoints, test_gray, test_keypoints, matches, test_gray, flags = 2)

# Display the best matching points
plt.rcParams['figure.figsize'] = [14.0, 7.0]
plt.title('Best Matching Points')
plt.imshow(result)
plt.show()

# Print total number of matching points between the training and query images
print("\nNumber of Matching Keypoints Between The Training and Query Images: ", len(matches))
```

```
[4] orb_test(img_color_1)
```

```
Number of Keypoints Detected In The Training Image:  500
Number of Keypoints Detected In The Query Image:  95
```

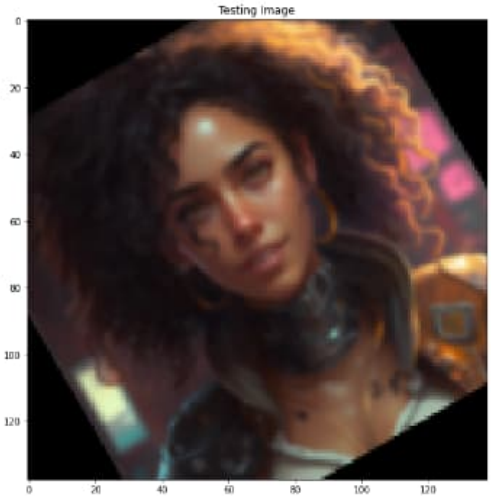


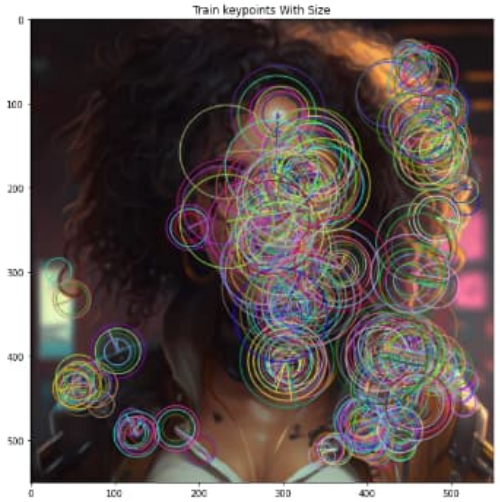


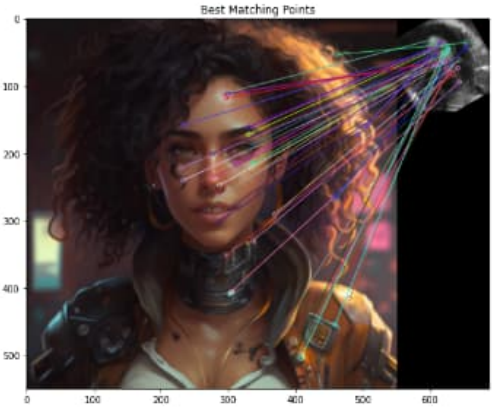

```
Number of Matching Keypoints Between The Training and Query Images:  45
```

```
[5] orb_test(img_color_2)
```

```
Number of Keypoints Detected In The Training Image:  500
Number of Keypoints Detected In The Query Image:  73
```



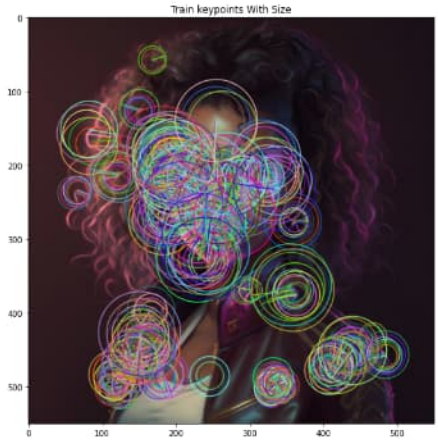


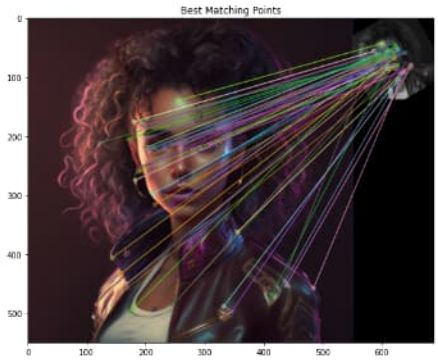



```
Number of Matching Keypoints Between The Training and Query Images:  44
```

```
[6] orb_test(img_color_3)
```

```
Number of Keypoints Detected In The Training Image:  500
Number of Keypoints Detected In The Query Image:  133
```

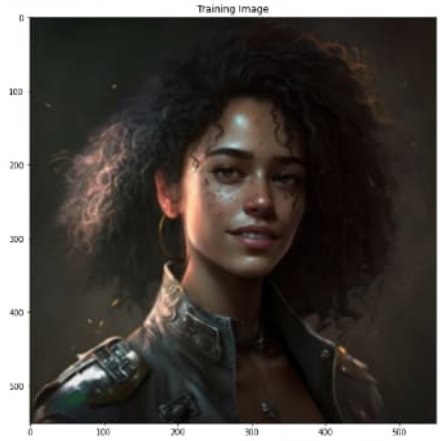


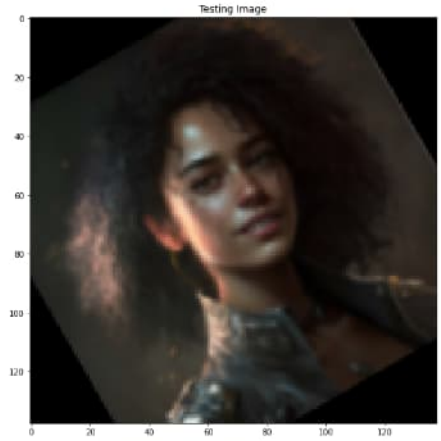


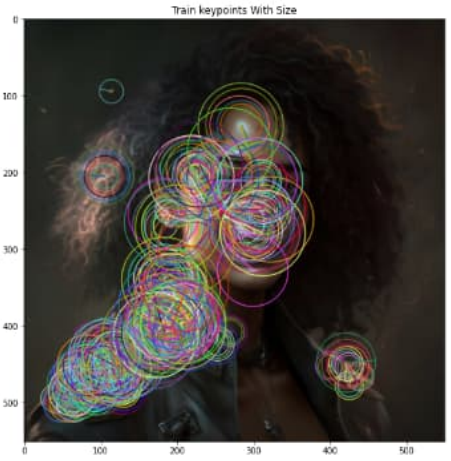

```
Number of Matching Keypoints Between The Training and Query Images:  56
```

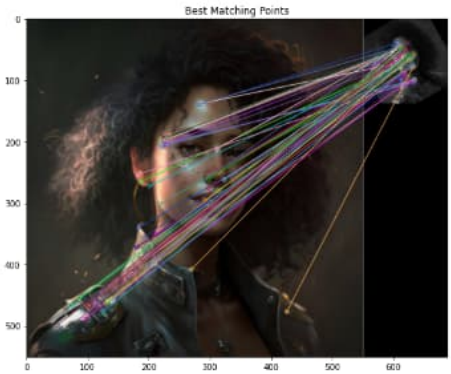
```
orb_test(img_color_4)
```

```
Number of Keypoints Detected In The Training Image:  500
Number of Keypoints Detected In The Query Image:  128
```



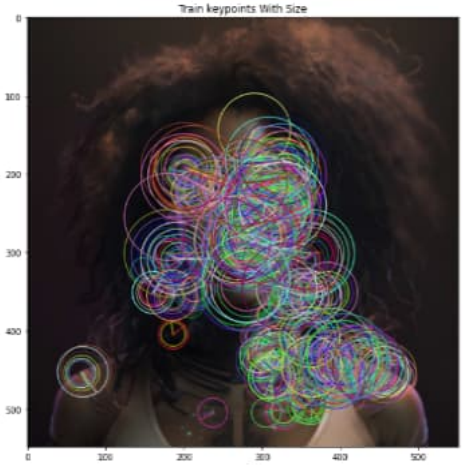


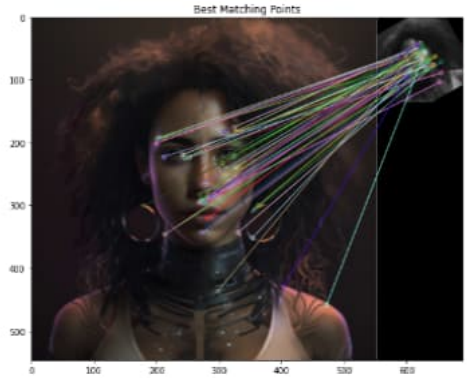




Number of Matching Keypoints Between The Training and Query Images: 63

[8] orb_test(img_color_5)

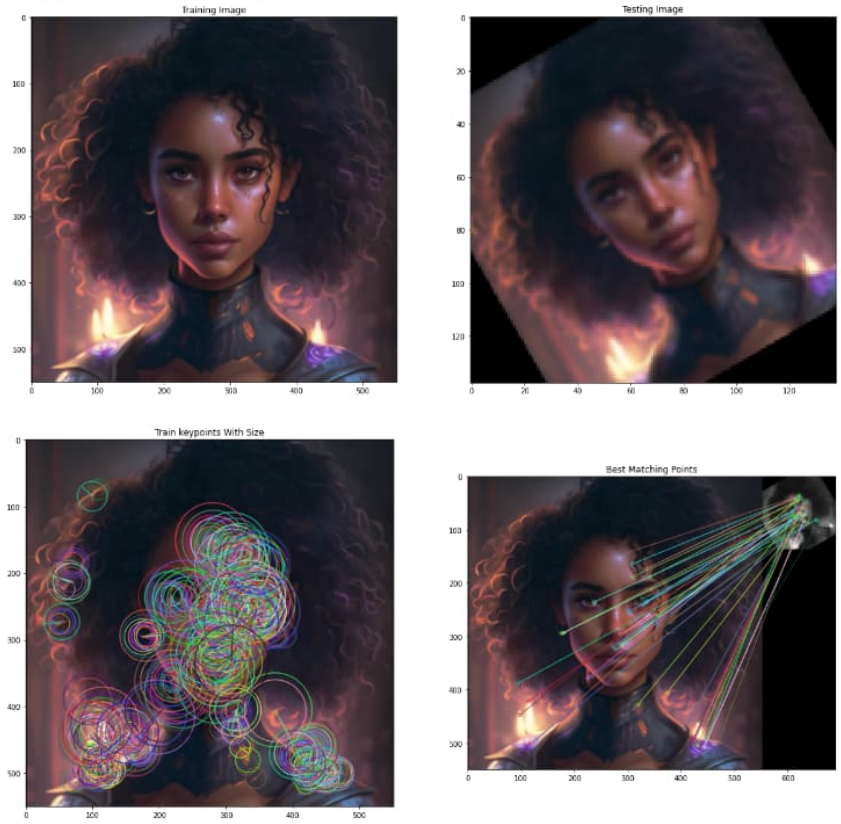




Number of Matching Keypoints Between The Training and Query Images: 52

```
[9] orb_test(img_color_6)
```

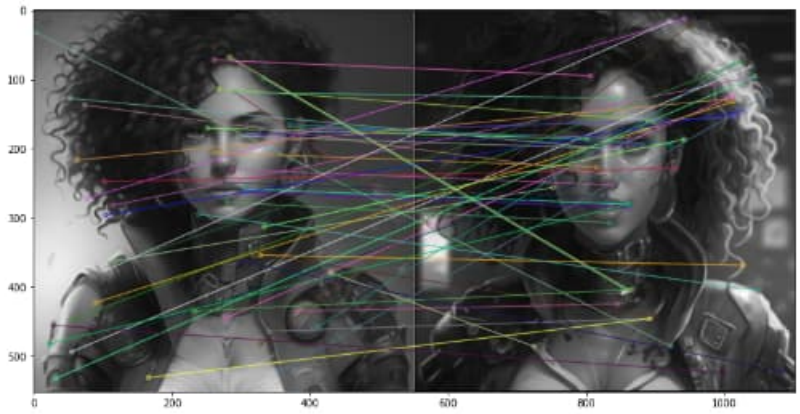
```
Number of Keypoints Detected In The Training Image:  500
Number of Keypoints Detected In The Query Image:  107
```



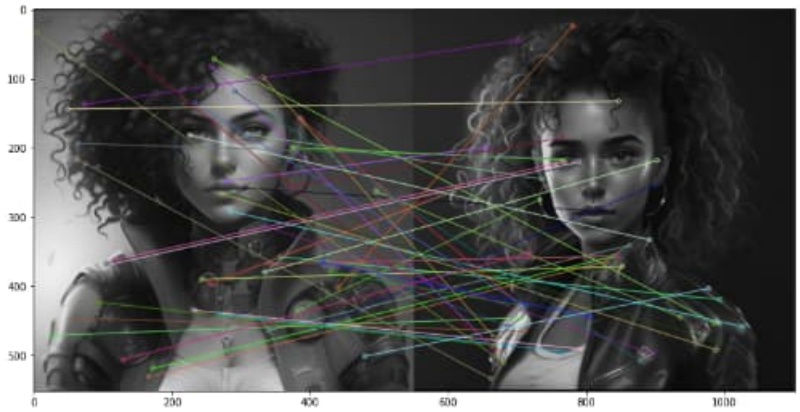
En los ejemplos anteriores observamos que se tienen matches entre 43 y 62 desde el imagen de Entrenamiento (Training) y la imagen a Evaluar (Test). Al estar utilizando el CrossChek = True en la función BF.Matcher, estamos tomando los mejores Keypoints y que nos ayudan a tener un mejor resultado. Dichos keypoints obtenidos, hacen un correcto match aun y cuando la imagen se encuentre rotada. Desde la forma del rostro de nuestra imagen (tomando en cuenta nariz, boca, dientes, pelo), hasta las prendas que utiliza.

```
[10] def sift_test(img1, img2):

       sift = cv2.SIFT_create()

       keypoints_1, descriptors_1 = sift.detectAndCompute(img1,None)
       keypoints_2, descriptors_2 = sift.detectAndCompute(img2,None)

       len(keypoints_1), len(keypoints_2)

       #feature matching
       bf = cv2.BFMatcher(cv2.NORM_L1, crossCheck=True) # crossCheck utilizado para comparar con las mejores Features

       matches = bf.match(descriptors_1,descriptors_2)
       matches = sorted(matches, key = lambda x:x.distance)

       img3 = cv2.drawMatches(img1, keypoints_1, img2, keypoints_2, matches[:50], img2, flags=2)
       plt.imshow(img3),plt.show()
```

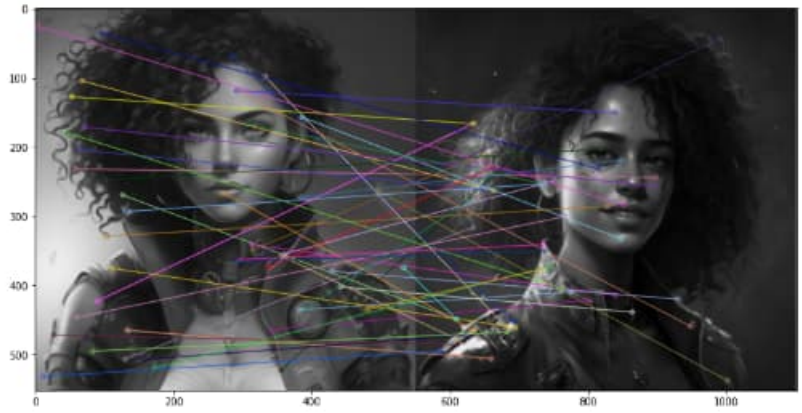
```
[11] sift_test(img_gray_1, img_gray_2)
```



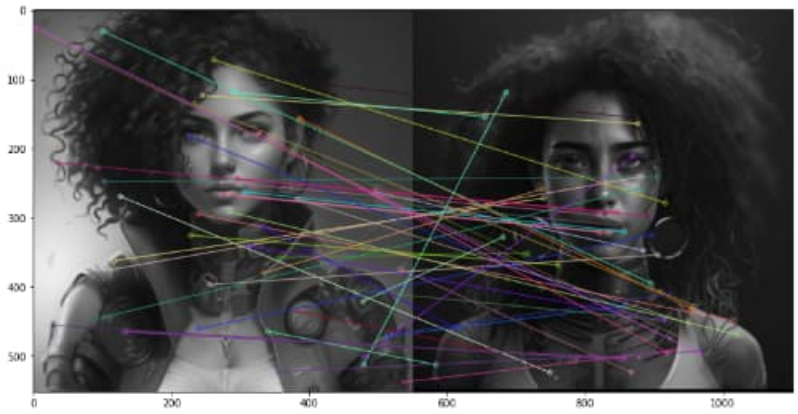

```
[12] sift_test(img_gray_1, img_gray_3)
```



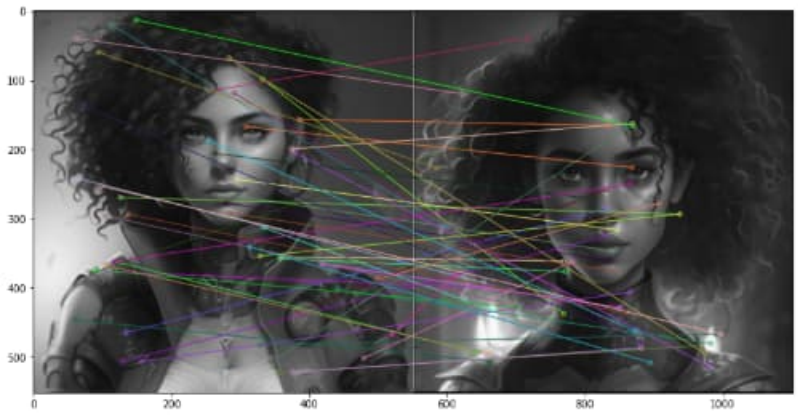

```
[13] sift_test(img_gray_1, img_gray_4)
```



```
[14] sift_test(img_gray_1, img_gray_5)
```




```
[15] sift_test(img_gray_1, img_gray_6)
```



En los ejemplos anteriores observamos que se tienen matches entre ambas imágenes, Entrenamiento (Training) y la imagen a Evaluar (Test).

En este ejercicio nos damos cuenta de que no es necesaria toda la información de la primer imagen para sacar las keypoint (puntos de interés) y poder hacer un match con la imagen a comparar. Dichos keypoints van desde la forma del rostro de nuestra imagen (tomando en cuenta nariz, boca, pelo), hasta las prendas que utiliza.

CONCLUSIÓN FINAL:

En lo que respecta al descriptor **SIFT**, observamos que la obtención de los puntos de interés se ejecutaron mas rápidamente en comparación con el descriptor ORB.

La ejecución del detector ORB fue "un poco" mas lenta que al ejecutar SIFT, investigando un poco mas del tema, encontramos que para la parte del descriptor **ORB** no se recomienda para trabajar con video en tiempo real, ya que consume mayor recurso del equipo.

En conclusión depende mucho de la aplicación con la que estemos trabajando para poder elegir alguno como el mejor descriptor, leyendo distintas citas en internet, encontramos que varios autores de decantan por uno o por otro como el mejor, para este ejercicio específico trabajó mas eficiente el SIFT, agregamos algunas referencias donde observamos algunos ejemplos en donde se hacen pruebas con ciertos ruidos, cambios de textura, etc.

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