# Feature Extraction and Object Detection

## OPENCV_CONTRIB INSTALLATION

[ ] ↳ *1 cell hidden*

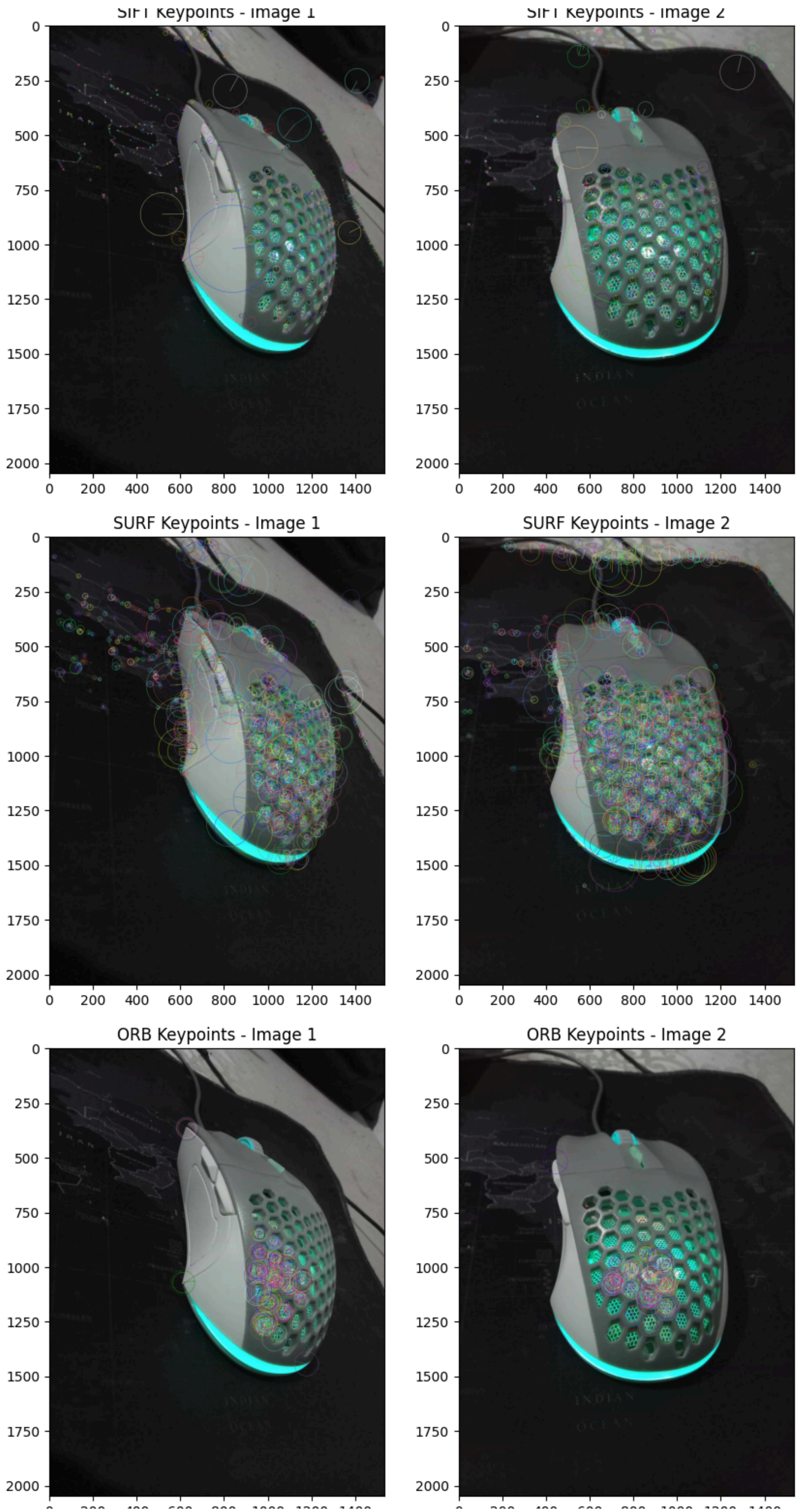
## Step 1: Load Images

[ ] ↳ *1 cell hidden*

## Step 2: Extract Keypoints and Descriptors Using SIFT, SURF, and ORB

```
import cv2
import matplotlib.pyplot as plt

# Convert images to grayscale
gray1 = cv2.cvtColor(image1, cv2.COLOR_BGR2GRAY)
gray2 = cv2.cvtColor(image2, cv2.COLOR_BGR2GRAY)

# Initialize feature detectors
# SIFT
sift = cv2.xfeatures2d.SIFT_create()

# SURF
surf = cv2.xfeatures2d.SURF_create(400)  # Hessian threshold set to 400

# ORB
orb = cv2.ORB_create(nfeatures=500)

# Detect keypoints and compute descriptors using SIFT
keypoints_sift_1, descriptors_sift_1 = sift.detectAndCompute(gray1, None)
keypoints_sift_2, descriptors_sift_2 = sift.detectAndCompute(gray2, None)

# Draw keypoints for SIFT
sift_image1 = cv2.drawKeypoints(image1, keypoints_sift_1, None, flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
sift_image2 = cv2.drawKeypoints(image2, keypoints_sift_2, None, flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)

# Save images showing SIFT keypoints
cv2.imwrite('sift_keypoints_1.jpg', sift_image1)
cv2.imwrite('sift_keypoints_2.jpg', sift_image2)

# Detect keypoints and compute descriptors using SURF
keypoints_surf_1, descriptors_surf_1 = surf.detectAndCompute(gray1, None)
keypoints_surf_2, descriptors_surf_2 = surf.detectAndCompute(gray2, None)

# Draw keypoints for SURF
surf_image1 = cv2.drawKeypoints(image1, keypoints_surf_1, None, flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
surf_image2 = cv2.drawKeypoints(image2, keypoints_surf_2, None, flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)

# Save images showing SURF keypoints
cv2.imwrite('surf_keypoints_1.jpg', surf_image1)
cv2.imwrite('surf_keypoints_2.jpg', surf_image2)

# Detect keypoints and compute descriptors using ORB
keypoints_orb_1, descriptors_orb_1 = orb.detectAndCompute(gray1, None)
keypoints_orb_2, descriptors_orb_2 = orb.detectAndCompute(gray2, None)

# Draw keypoints for ORB
orb_image1 = cv2.drawKeypoints(image1, keypoints_orb_1, None, flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
orb_image2 = cv2.drawKeypoints(image2, keypoints_orb_2, None, flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)

# Save images showing ORB keypoints
cv2.imwrite('orb_keypoints_1.jpg', orb_image1)
cv2.imwrite('orb_keypoints_2.jpg', orb_image2)

# Display the processed images
def display_images(title, img1, img2):
    img1_rgb = cv2.cvtColor(img1, cv2.COLOR_BGR2RGB)
    img2_rgb = cv2.cvtColor(img2, cv2.COLOR_BGR2RGB)
```

```
        plt.figure(figsize=(10, 6))
        plt.subplot(1, 2, 1)
        plt.title(f'{title} - Image 1')
        plt.imshow(img1_rgb)
        plt.subplot(1, 2, 2)
        plt.title(f'{title} - Image 2')
        plt.imshow(img2_rgb)
        plt.show()

    # Display SIFT, SURF, and ORB keypoints
    display_images('SIFT Keypoints', sift_image1, sift_image2)
    display_images('SURF Keypoints', surf_image1, surf_image2)
    display_images('ORB Keypoints', orb_image1, orb_image2)
```

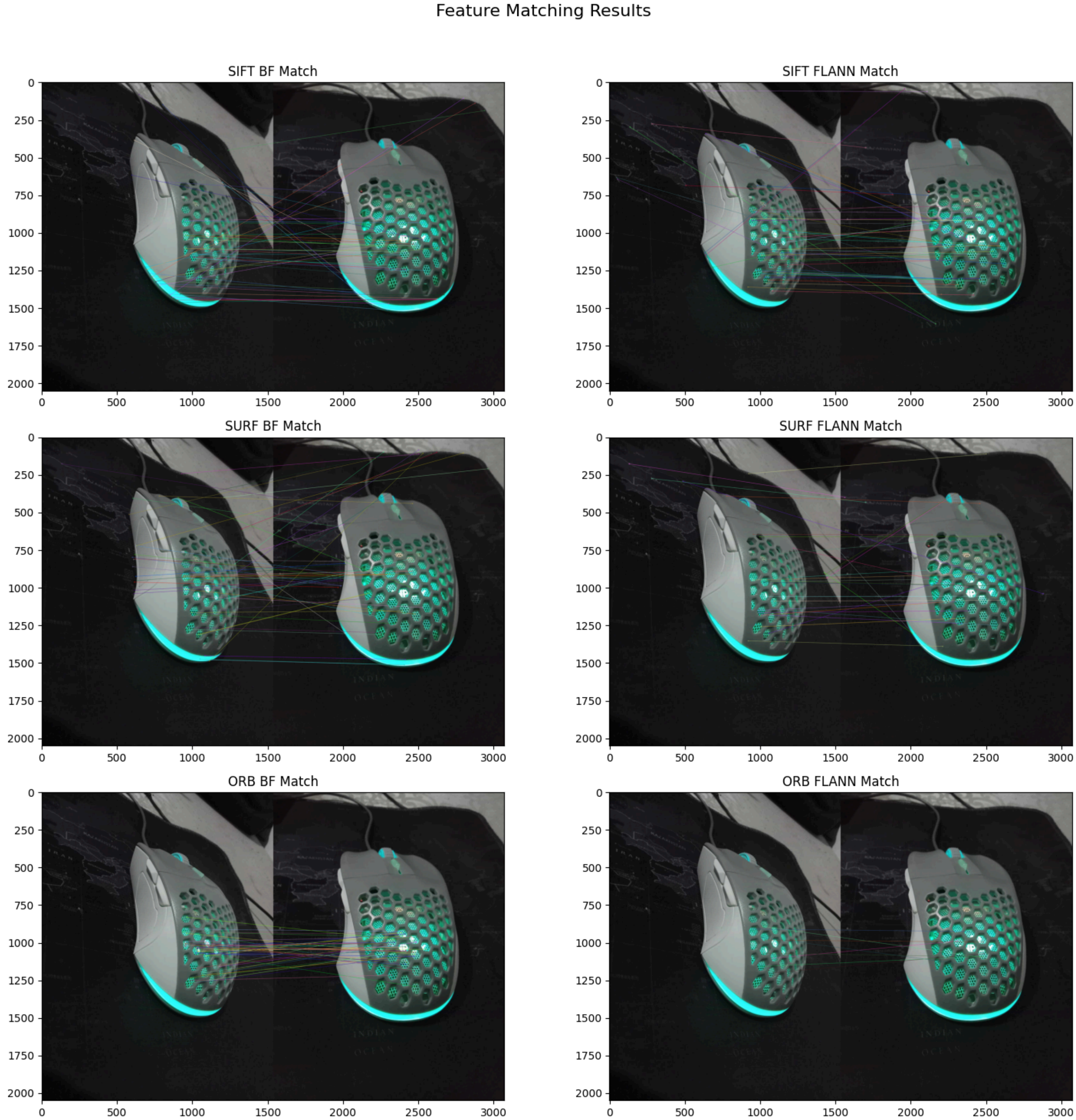

SIFT Keypoints - Image 1
SIFT Keypoints - Image 2
SURF Keypoints - Image 1
SURF Keypoints - Image 2
ORB Keypoints - Image 1
ORB Keypoints - Image 2
0
250
500
750
1000
1250
1500
1750
2000
0
200
400
600
800
1000
1200
1400

0 200 400 600 800 1000 1200 1400 0 200 400 600 800 1000 1200 1400

## Step 3: Feature Matching with Brute-Force and FLANN

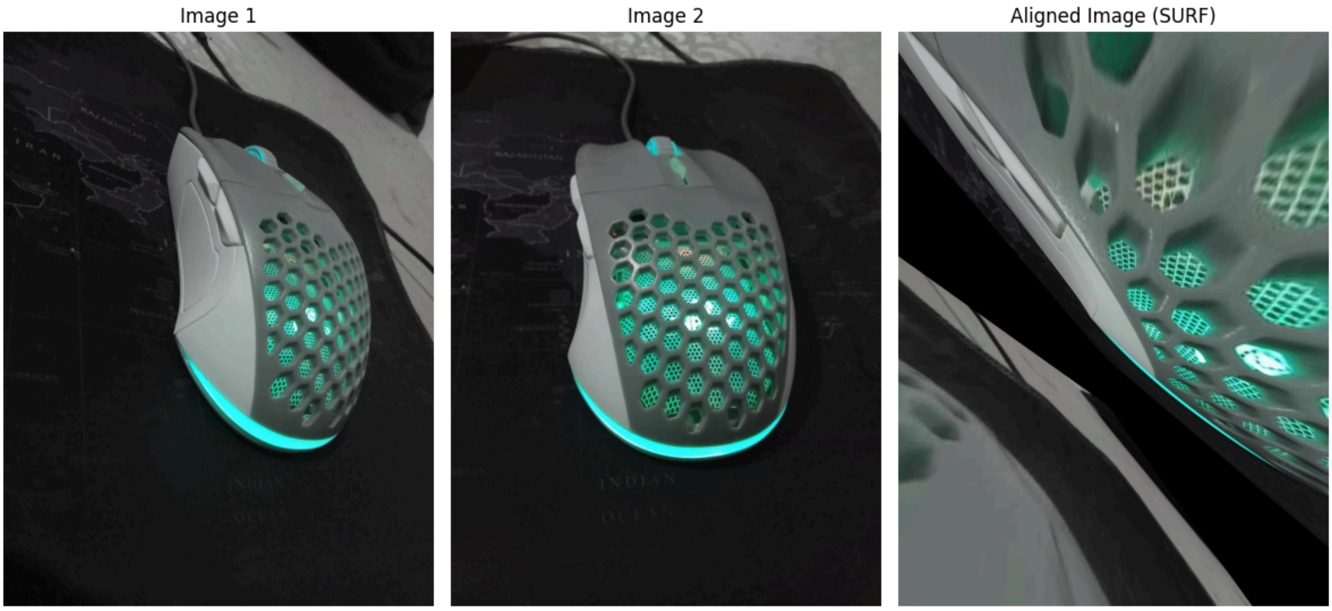
```
# Function to match features using Brute-Force Matcher
def brute_force_matcher(descriptors1, descriptors2, keypoints1, keypoints2, img1, img2):
    bf = cv2.BFMatcher(cv2.NORM_L2, crossCheck=True)  # Using L2 norm for SIFT and SURF
    matches = bf.match(descriptors1, descriptors2)
    matches = sorted(matches, key=lambda x: x.distance)
    matched_image = cv2.drawMatches(img1, keypoints1, img2, keypoints2, matches[:50], None, flags=cv2.DrawMatchesFlags_NOT_DRAW
    return matched_image

# Function to match features using FLANN Matcher
def flann_matcher(descriptors1, descriptors2, keypoints1, keypoints2, img1, img2):
    index_params = dict(algorithm=1, trees=5)  # Using KD-Tree (algorithm=1)
    search_params = dict(checks=50)
    flann = cv2.FlannBasedMatcher(index_params, search_params)
    matches = flann.knnMatch(descriptors1, descriptors2, k=2)
    # Apply ratio test as per Lowe's paper
    good_matches = []
    for m, n in matches:
        if m.distance < 0.7 * n.distance:
            good_matches.append(m)
    matched_image = cv2.drawMatches(img1, keypoints1, img2, keypoints2, good_matches[:50], None, flags=cv2.DrawMatchesFlags_NOT
    return matched_image

# Brute-Force Matching and FLANN Matching for SIFT
sift_bf_image = brute_force_matcher(descriptors_sift_1, descriptors_sift_2, keypoints_sift_1, keypoints_sift_2, image1, image2)
sift_flann_image = flann_matcher(descriptors_sift_1, descriptors_sift_2, keypoints_sift_1, keypoints_sift_2, image1, image2)

# Brute-Force Matching and FLANN Matching for SURF
surf_bf_image = brute_force_matcher(descriptors_surf_1, descriptors_surf_2, keypoints_surf_1, keypoints_surf_2, image1, image2)
surf_flann_image = flann_matcher(descriptors_surf_1, descriptors_surf_2, keypoints_surf_1, keypoints_surf_2, image1, image2)

# Brute-Force Matching for ORB (uses Hamming distance instead of L2)
bf_orb = cv2.BFMatcher(cv2.NORM_HAMMING, crossCheck=True)
orb_matches = bf_orb.match(descriptors_orb_1, descriptors_orb_2)
orb_matches = sorted(orb_matches, key=lambda x: x.distance)
orb_bf_image = cv2.drawMatches(image1, keypoints_orb_1, image2, keypoints_orb_2, orb_matches[:50], None, flags=cv2.DrawMatchesF

# FLANN Matching for ORB (FLANN does not directly support Hamming, so approximate)
index_params = dict(algorithm=6,  # FLANN_INDEX_LSH for ORB
                    table_number=6,
                    key_size=12,
                    multi_probe_level=1)
search_params = dict(checks=50)  # Set search_params
flann_orb = cv2.FlannBasedMatcher(index_params, search_params)
orb_matches = flann_orb.knnMatch(descriptors_orb_1, descriptors_orb_2, k=2)

# Apply ratio test as per Lowe's paper
good_matches_orb = []
for m, n in orb_matches:
    if m.distance < 0.7 * n.distance:
        good_matches_orb.append(m)

orb_flann_image = cv2.drawMatches(image1, keypoints_orb_1, image2, keypoints_orb_2, good_matches_orb[:50], None, flags=cv2.Draw

# Display the processed images in a 2-column, 3-row layout
fig, axes = plt.subplots(3, 2, figsize=(15, 15))
fig.suptitle("Feature Matching Results", fontsize=16)

images = [
    ("SIFT BF Match", sift_bf_image),
    ("SIFT FLANN Match", sift_flann_image),
    ("SURF BF Match", surf_bf_image),
    ("SURF FLANN Match", surf_flann_image),
    ("ORB BF Match", orb_bf_image),
    ("ORB FLANN Match", orb_flann_image)
]

for i, (title, img) in enumerate(images):
    row, col = divmod(i, 2)
    img_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    axes[row, col].imshow(img_rgb)
    axes[row, col].set_title(title)
```

```
plt.tight_layout(rect=[0, 0, 1, 0.96])  # Adjust layout to fit title
plt.show()
```



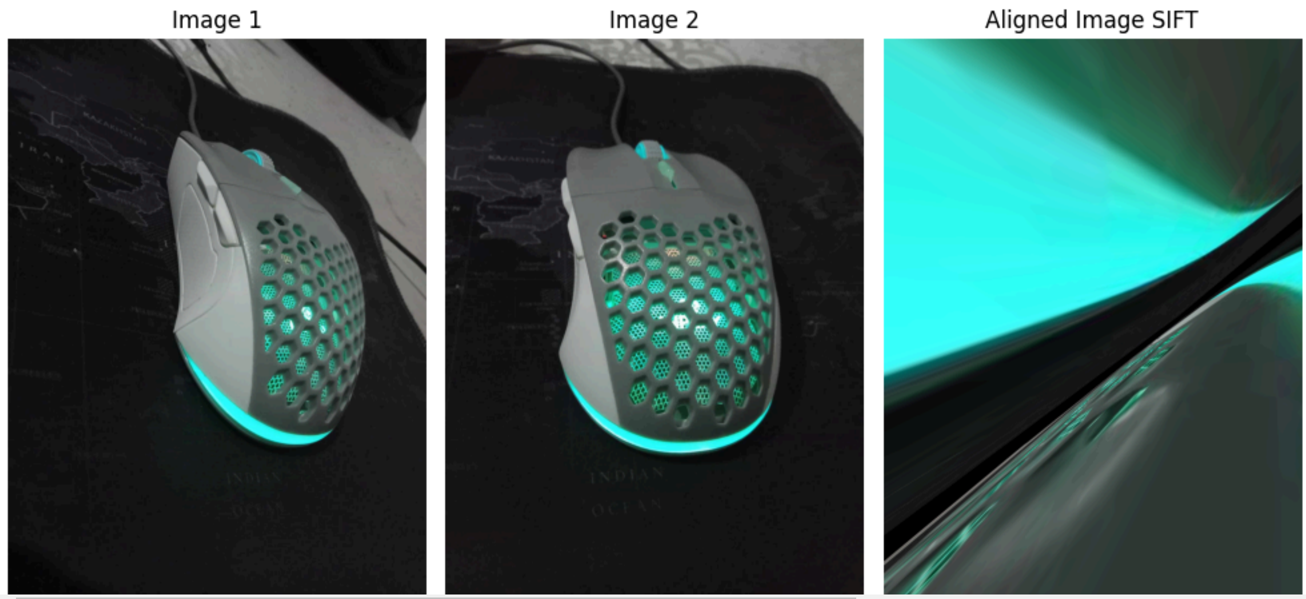
## Step 4: Image Alignment Using Homography

```
import numpy as np

# Detect keypoints and compute descriptors using SURF
keypoints1, descriptors1 = surf.detectAndCompute(gray1, None)
keypoints2, descriptors2 = surf.detectAndCompute(gray2, None)

# Use Brute-Force Matcher to find matches
bf = cv2.BFMatcher(cv2.NORM_L2, crossCheck=True)
matches = bf.match(descriptors1, descriptors2)
matches = sorted(matches, key=lambda x: x.distance)

# Extract location of good matches
points1 = np.zeros((len(matches), 2), dtype=np.float32)
points2 = np.zeros((len(matches), 2), dtype=np.float32)

for i, match in enumerate(matches):
    points1[i, :] = keypoints1[match.queryIdx].pt
    points2[i, :] = keypoints2[match.trainIdx].pt

# Compute homography matrix using RANSAC
H, mask = cv2.findHomography(points1, points2, cv2.RANSAC)

# Use the homography matrix to warp image1 to align with image2
height, width, channels = image2.shape
aligned_image = cv2.warpPerspective(image1, H, (width, height))

# Save and display the aligned and warped image
cv2.imwrite('aligned_image_surf.jpg', aligned_image)

# Plot the original and aligned images for comparison
plt.figure(figsize=(12, 8))

# Convert BGR to RGB for displaying using matplotlib
image1_rgb = cv2.cvtColor(image1, cv2.COLOR_BGR2RGB)
image2_rgb = cv2.cvtColor(image2, cv2.COLOR_BGR2RGB)
aligned_image_surf = cv2.cvtColor(aligned_image, cv2.COLOR_BGR2RGB)

# Plot original image, target image, and aligned image
plt.subplot(1, 3, 1)
plt.title("Image 1")
plt.imshow(image1_rgb)
plt.axis('off')

plt.subplot(1, 3, 2)
plt.title("Image 2")
plt.imshow(image2_rgb)
plt.axis('off')

plt.subplot(1, 3, 3)
plt.title("Aligned Image (SURF)")
plt.imshow(aligned_image_surf)
plt.axis('off')

plt.tight_layout()
plt.show()
```




```
# Detect keypoints and compute descriptors using SIFT
keypoints1, descriptors1 = sift.detectAndCompute(gray1, None)
keypoints2, descriptors2 = sift.detectAndCompute(gray2, None)

# Use Brute-Force Matcher to find matches
bf = cv2.BFMatcher(cv2.NORM_L2, crossCheck=True)
matches = bf.match(descriptors1, descriptors2)
matches = sorted(matches, key=lambda x: x.distance)

# Extract location of good matches
points1 = np.zeros((len(matches), 2), dtype=np.float32)
points2 = np.zeros((len(matches), 2), dtype=np.float32)

for i, match in enumerate(matches):
    points1[i, :] = keypoints1[match.queryIdx].pt
    points2[i, :] = keypoints2[match.trainIdx].pt

# Compute homography matrix using RANSAC
H, mask = cv2.findHomography(points1, points2, cv2.RANSAC)

# Use the homography matrix to warp image1 to align with image2
height, width, channels = image2.shape
aligned_image = cv2.warpPerspective(image1, H, (width, height))

# Save and display the aligned and warped image
cv2.imwrite('aligned_image.jpg', aligned_image)

# Plot the original and aligned images for comparison
plt.figure(figsize=(10, 10))

# Convert BGR to RGB for displaying using matplotlib
image1_rgb = cv2.cvtColor(image1, cv2.COLOR_BGR2RGB)
image2_rgb = cv2.cvtColor(image2, cv2.COLOR_BGR2RGB)
aligned_image_rgb = cv2.cvtColor(aligned_image, cv2.COLOR_BGR2RGB)

# Plot original image, target image, and aligned image
plt.subplot(1, 3, 1)
plt.title("Image 1")
plt.imshow(image1_rgb)
plt.axis('off')

plt.subplot(1, 3, 2)
plt.title("Image 2")
plt.imshow(image2_rgb)
plt.axis('off')

plt.subplot(1, 3, 3)
plt.title("Aligned Image SIFT")
plt.imshow(aligned_image_rgb)
```

```
plt.axis('off')

plt.tight_layout()
plt.show()
```




## Step 5: Performance Analysis

```
import cv2
import time

# Define a function to extract keypoints and descriptors using different algorithms
def extract_features(detector, image1, image2):
    start_time = time.time()
    keypoints1, descriptors1 = detector.detectAndCompute(image1, None)
    keypoints2, descriptors2 = detector.detectAndCompute(image2, None)
    end_time = time.time()
    time_taken = end_time - start_time
    return keypoints1, descriptors1, keypoints2, descriptors2, time_taken

# Initialize detectors
sift = cv2.xfeatures2d.SIFT_create()
surf = cv2.xfeatures2d.SURF_create(hessianThreshold=400)
orb = cv2.ORB_create()

# Extract features using SIFT
sift_keypoints1, sift_descriptors1, sift_keypoints2, sift_descriptors2, sift_time = extract_features(sift, image1, image2)
print(f"SIFT: Number of keypoints in image1: {len(sift_keypoints1)}, image2: {len(sift_keypoints2)}, Time: {sift_time:.2f} sec'

# Extract features using SURF
surf_keypoints1, surf_descriptors1, surf_keypoints2, surf_descriptors2, surf_time = extract_features(surf, image1, image2)
print(f"SURF: Number of keypoints in image1: {len(surf_keypoints1)}, image2: {len(surf_keypoints2)}, Time: {surf_time:.2f} sec'

# Extract features using ORB
orb_keypoints1, orb_descriptors1, orb_keypoints2, orb_descriptors2, orb_time = extract_features(orb, image1, image2)
print(f"ORB: Number of keypoints in image1: {len(orb_keypoints1)}, image2: {len(orb_keypoints2)}, Time: {orb_time:.2f} sec")

# Function to match descriptors using Brute-Force Matcher and FLANN Matcher
def match_features(descriptor1, descriptor2, matcher_type='BF', norm_type=cv2.NORM_L2):
    if matcher_type == 'BF':
        bf = cv2.BFMatcher(norm_type, crossCheck=True)
        start_time = time.time()
        matches = bf.match(descriptor1, descriptor2)
        end_time = time.time()
    elif matcher_type == 'FLANN':
        index_params = dict(algorithm=1, trees=5) if norm_type == cv2.NORM_L2 else dict(algorithm=6)
        search_params = dict(checks=50)
        flann = cv2.FlannBasedMatcher(index_params, search_params)
        start_time = time.time()
        try:
            matches = flann.knnMatch(descriptor1, descriptor2, k=2)
            # Apply ratio test for FLANN Matcher
            good_matches = []
```

```
            for m, n in matches:
                if m.distance < 0.7 * n.distance:
                    good_matches.append(m)
            matches = good_matches
        except ValueError:
            print("Not enough matches found for FLANN.")
            matches = []
        end_time = time.time()

    time_taken = end_time - start_time
    return matches, time_taken

# Compare SIFT feature matching with BF and FLANN Matcher
sift_bf_matches, sift_bf_time = match_features(sift_descriptors1, sift_descriptors2, matcher_type='BF')
sift_flann_matches, sift_flann_time = match_features(sift_descriptors1, sift_descriptors2, matcher_type='FLANN')

print(f"SIFT + BF: Number of matches: {len(sift_bf_matches)}, Time: {sift_bf_time:.2f} sec")
print(f"SIFT + FLANN: Number of matches: {len(sift_flann_matches)}, Time: {sift_flann_time:.2f} sec")

# Compare SURF feature matching with BF and FLANN Matcher
surf_bf_matches, surf_bf_time = match_features(surf_descriptors1, surf_descriptors2, matcher_type='BF')
surf_flann_matches, surf_flann_time = match_features(surf_descriptors1, surf_descriptors2, matcher_type='FLANN')

print(f"SURF + BF: Number of matches: {len(surf_bf_matches)}, Time: {surf_bf_time:.2f} sec")
print(f"SURF + FLANN: Number of matches: {len(surf_flann_matches)}, Time: {surf_flann_time:.2f} sec")

# Compare ORB feature matching with BF and FLANN Matcher
orb_bf_matches, orb_bf_time = match_features(orb_descriptors1, orb_descriptors2, matcher_type='BF', norm_type=cv2.NORM_HAMMING)
orb_flann_matches, orb_flann_time = match_features(orb_descriptors1, orb_descriptors2, matcher_type='FLANN', norm_type=cv2.NORM

print(f"ORB + BF: Number of matches: {len(orb_bf_matches)}, Time: {orb_bf_time:.2f} sec")
print(f"ORB + FLANN: Number of matches: {len(orb_flann_matches)}, Time: {orb_flann_time:.2f} sec")
```

```
SIFT: Number of keypoints in image1: 2756, image2: 5053, Time: 2.52 sec
SURF: Number of keypoints in image1: 1459, image2: 2546, Time: 2.39 sec
ORB: Number of keypoints in image1: 500, image2: 500, Time: 0.08 sec
SIFT + BF: Number of matches: 941, Time: 0.78 sec
SIFT + FLANN: Number of matches: 52, Time: 0.12 sec
SURF + BF: Number of matches: 481, Time: 0.11 sec
SURF + FLANN: Number of matches: 28, Time: 0.05 sec
Not enough matches found for FLANN.
ORB + BF: Number of matches: 137, Time: 0.01 sec
ORB + FLANN: Number of matches: 0, Time: 0.01 sec
```

```
performance_analysis = """
Performance Analysis

1. Keypoint Detection:
- SIFT: Detected {sift_kp1} keypoints in image1 and {sift_kp2} in image2. It took {sift_time:.2f} seconds.
- SURF: Detected {surf_kp1} keypoints in image1 and {surf_kp2} in image2. It took {surf_time:.2f} seconds.
- ORB: Detected {orb_kp1} keypoints in both images. It took {orb_time:.2f} seconds.

2. Feature Matching:
- SIFT:
  - Brute-Force: Found {sift_bf_matches} matches in {sift_bf_time:.2f} seconds.
  - FLANN: Found {sift_flann_matches} matches in {sift_flann_time:.2f} seconds.
- SURF:
  - Brute-Force: Found {surf_bf_matches} matches in {surf_bf_time:.2f} seconds.
  - FLANN: Found {surf_flann_matches} matches in {surf_flann_time:.2f} seconds.
- ORB:
  - Brute-Force: Found {orb_bf_matches} matches in {orb_bf_time:.2f} seconds.
  - FLANN: Found {orb_flann_matches} matches in {orb_flann_time:.2f} seconds.

Observations and Conclusions:

1. Keypoint Detection:
- SIFT provided the highest number of keypoints detected in both images, indicating its effectiveness in identifying features i
- SURF showed a reasonable number of keypoints but was less effective than SIFT. This is expected as SURF is designed to be fas
- ORB detected the least number of keypoints, which is typical for this algorithm as it focuses on speed and efficiency, suitab

2. Feature Matching:
- SIFT performed significantly better in matching, with a high number of matches using both matchers, particularly the Brute-Fo
- SURF had a decent number of matches using Brute-Force but dropped significantly with FLANN. The few matches found may indicat
- ORB had very few matches overall. It performed well with the Brute-Force matcher but failed to find any matches with FLANN, s

3. Speed:
- ORB is the fastest algorithm, making it suitable for applications where speed is crucial, although this comes at the expense
- Both SIFT and SURF were comparable in time, with SIFT slightly slower due to its more complex calculations.
```