

CSc 8830: CV Assignment-2 Solutions Report

Capture a 10 sec video footage using a camera of your choice. The footage should be taken with the camera in hand and you need to pan the camera slightly from left-right or right-left during the 10 sec duration. For all the images, operate at grayscale unless otherwise specified:

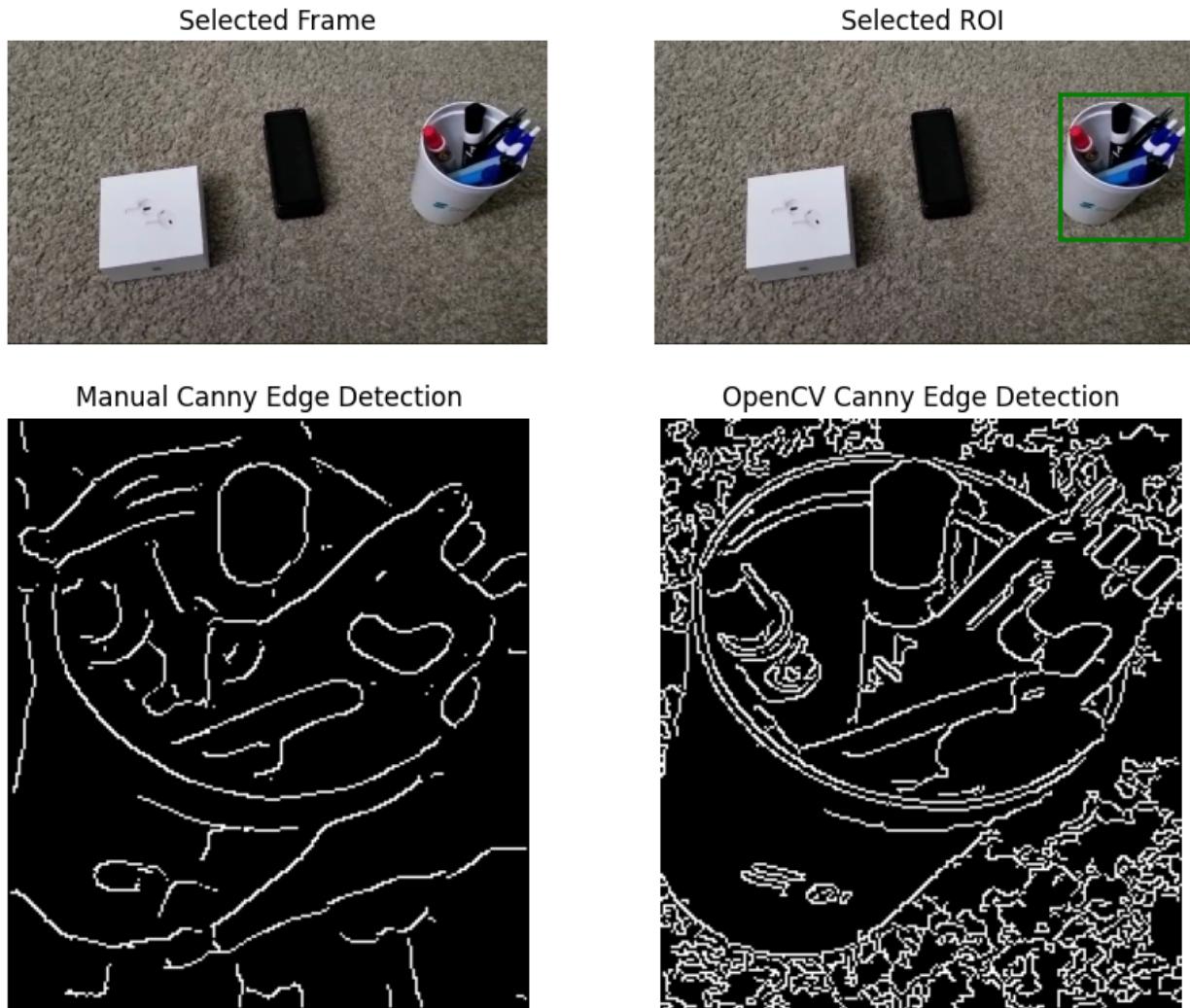
A video of 10 sec was recorded from a mobile camera with 1030p resolution and 30FPS frame rate.

1. Pick any image frame from the 10 sec video footage. Pick a region of interest in the image making sure there is an EDGE in that region. Pick a 5 x 5 image patch in that region that constitutes the edge. Perform the steps of CANNY EDGE DETECTION manually and note the pixels that correspond to the EDGE. Compare the outcome with MATLAB or OpenCV or DepthAI's Canny edge detection function.

Steps Involved:

1. **Pick an Image Frame:** Select a frame from the video footage that contains the region of interest with an edge.
2. **Select Region of Interest (ROI):** Identify the area in the image where the edge is located. Ensure that this region contains a clear edge that you want to detect.
3. **Pick a 5x5 Image Patch:** Within the ROI, select a 5x5 image patch that includes the edge. This patch will be used for manual edge detection.
4. **Convert to Grayscale:** Convert the selected image patch to grayscale. Edge detection algorithms typically work on grayscale images.
5. **Compute Image Gradient:** Use a simple gradient operator (e.g., Sobel operator) to compute the gradient magnitude and direction at each pixel in the image patch. This step highlights areas of rapid intensity change, which often correspond to edges.
6. **Apply Non-Maximum Suppression:** Suppress non-maximum pixels along the gradient direction. Only keep pixels that have the maximum gradient magnitude in their local neighborhood.
7. **Apply Hysteresis Thresholding:** Apply hysteresis thresholding to the gradient magnitude image to identify strong and weak edges. Pixels with gradient magnitudes above a high threshold are considered strong edges, while pixels between high and low thresholds are considered weak edges.
8. **Edge Tracking by Hysteresis:** Perform edge tracking by hysteresis to link weak edges to strong edges. Starting from strong edge pixels, follow the gradient direction and connect neighboring weak edge pixels that are part of the same edge.

9. **Note Detected Edge Pixels:** Note down the pixels that correspond to the detected edge in the 5x5 image patch.
10. **Compare with OpenCV:** Use OpenCV Canny edge detection function to perform edge detection on the same image patch. Compare the outcome with the manually detected edge pixels to assess the accuracy and effectiveness of the manual process.



2. Pick any image frame from the 10 sec video footage. Pick a region of interest in the image making sure there is a CORNER in that region. Pick a 5 x 5 image patch in that region that constitutes the edge. Perform the steps of HARRIS CORNER DETECTION manually and note the pixels that correspond to the CORNER. Compare the outcome with MATLAB or OpenCV or DepthAI's Harris corner detection function.

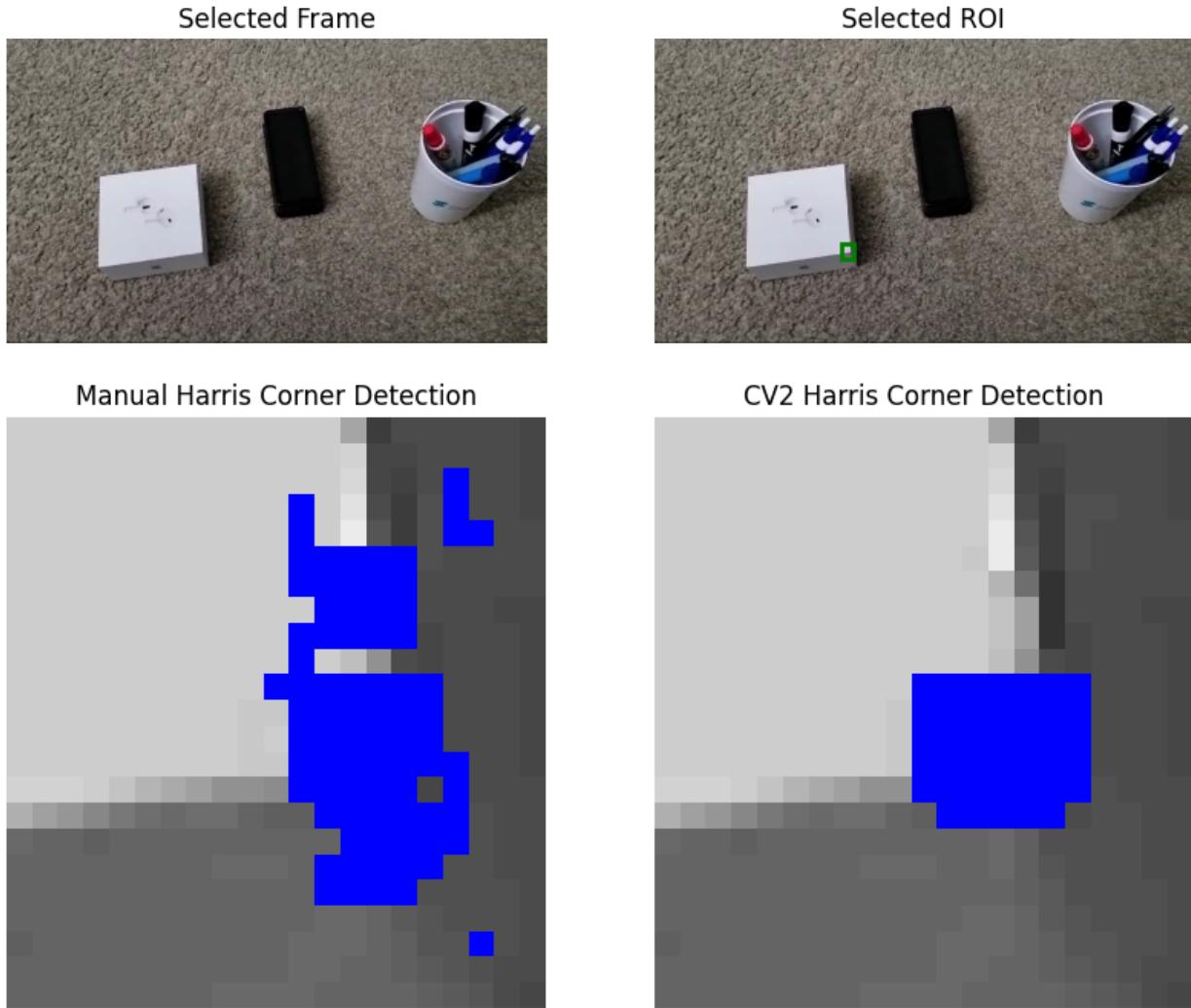
Steps Involved:

- Pick an Image Frame:** Select a frame from the video footage that contains the region of interest with a corner.
- Select Region of Interest (ROI):** Identify the area in the image where the corner is located. Ensure that this region contains a clear corner that you want to detect.
- Pick a 5x5 Image Patch:** Within the ROI, select a 5x5 image patch that includes the corner. This patch will be used for manual corner detection.
- Convert to Grayscale:** Convert the selected image patch to grayscale. Corner detection algorithms typically work on grayscale images.
- Compute Gradient:** Compute the gradient of the grayscale image patch using a gradient operator such as the Sobel operator. This step helps in identifying areas of rapid intensity change.
- Compute Harris Corner Response:** Compute the Harris corner response function for each pixel in the image patch using the formula:

$$R = \det(M) - k \cdot (\text{trace}(M))^2$$

Where:

- R is the Harris corner response.
 - M is the gradient matrix of the image patch.
 - $\det(M)$ is the determinant of M .
 - $\text{trace}(M)$ is the trace of M .
 - k is an empirical constant typically set to a small value like 0.04.
- Threshold Harris Response:** Apply a threshold to the computed Harris corner response to identify potential corner pixels. Pixels with a response above a certain threshold are considered potential corners.
 - Perform Non-Maximum Suppression:** Perform non-maximum suppression to eliminate non-maximum responses and identify local maxima as corner candidates.
 - Note Detected Corner Pixels:** Note down the pixels that correspond to the detected corners in the 5x5 image patch.
 - Compare with OpenCV:** Use OpenCV Harris corner detection function to perform corner detection on the same image patch. Compare the outcome with the manually detected corner pixels to assess the accuracy and effectiveness of the manual process.



3. Consider an image pair from your footage where the images are separated by at least 2 seconds. Also ensure there is at least some overlap of scenes in the two images.

- Pick a pixel (super-pixel patch as discussed in class) on image 1 and a corresponding pixel ((super-pixel patch as discussed in class)) on image 2 (the pixel on image 2 that corresponds to the same object area on image 1). Compute the SIFT feature for each of these 2 patches. Compute the sum of squared difference (SSD) value between the SIFT vector for these two pixels. Use MATLAB or Python or C++ implementation -- The MATLAB code for SIFT feature extraction and matching can be downloaded from here: <https://www.cs.ubc.ca/~lowe/keypoints/> (Please first read the ReadMe document in the folder to find instructions to execute the code).
 - Compute the Homography matrix between these two images using MATLAB or Python or C++ implementation. Compute its inverse.
- Select Image Pair:** Choose two images from your footage that are separated by at least 2

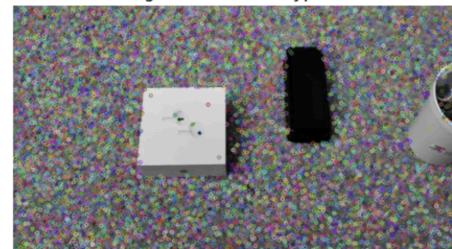
seconds and have some overlap of scenes.

2. **Select Corresponding Pixels:** Pick a pixel (super-pixel patch) in the first image and its corresponding pixel in the second image. Ensure that the corresponding pixels represent the same object or area in the scene.
3. **Compute SIFT Features:** Use MATLAB, Python (with OpenCV), or C++ (with OpenCV) to compute the SIFT features for the selected super-pixel patches in both images. This involves detecting keypoints and computing descriptors using the SIFT algorithm.
4. **Calculate SSD:** Compute the sum of squared differences (SSD) between the SIFT descriptors of the two super-pixel patches. This quantifies the dissimilarity between the two patches based on their feature vectors.
5. **Compute Homography Matrix:** Use MATLAB, Python (with OpenCV), or C++ (with OpenCV) to compute the homography matrix that transforms points from the coordinate system of the first image to the coordinate system of the second image. This can be done using feature matching and the RANSAC algorithm to estimate the homography matrix robustly.
6. **Compute Inverse Homography Matrix:** Once the homography matrix is computed, calculate its inverse. This will allow you to transform points from the coordinate system of the second image back to the coordinate system of the first image.
7. **Perform the Computations:** Implement the above steps in your chosen programming language (Python). Use existing libraries or implementations for SIFT feature extraction and homography estimation if available.

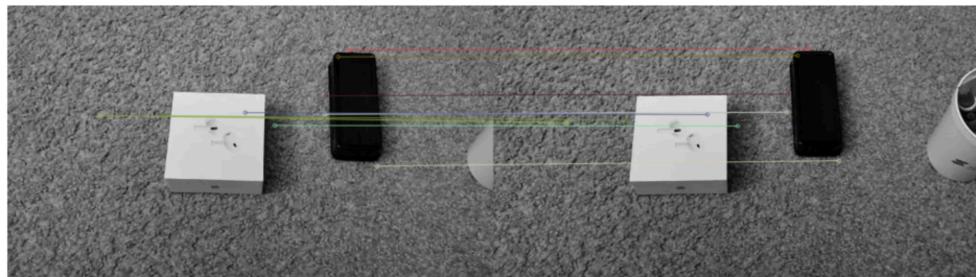
Image 1 with SIFT Keypoints



Image 2 with SIFT Keypoints



Best Matches with SIFT



Sum of Squared Difference (SSD) between SIFT vectors: 1425.0

Two frames with at least 2-second difference were selected.

Homography Matrix:

```
[ [-8.87860525e+00 -1.07937893e+01  4.08755449e+03]
 [ -1.21440619e+00 -1.04243070e+01  1.60691053e+03]
 [ -5.97664703e-03 -1.74197323e-02  1.00000000e+00]]
```

Inverse of Homography Matrix:

```
[ [-7.51990911e-02  2.58589073e-01 -1.08149122e+02]
 [  3.59117641e-02 -6.65678901e-02 -3.98226494e+01]
 [  1.76134892e-04  3.85900794e-04 -3.40069019e-01]]
```

4. Implement an application that will compute and display the INTEGRAL image feed along with the RGB feed. You cannot use a built-in function such as “output = integral_image(input)”

Steps Involved:

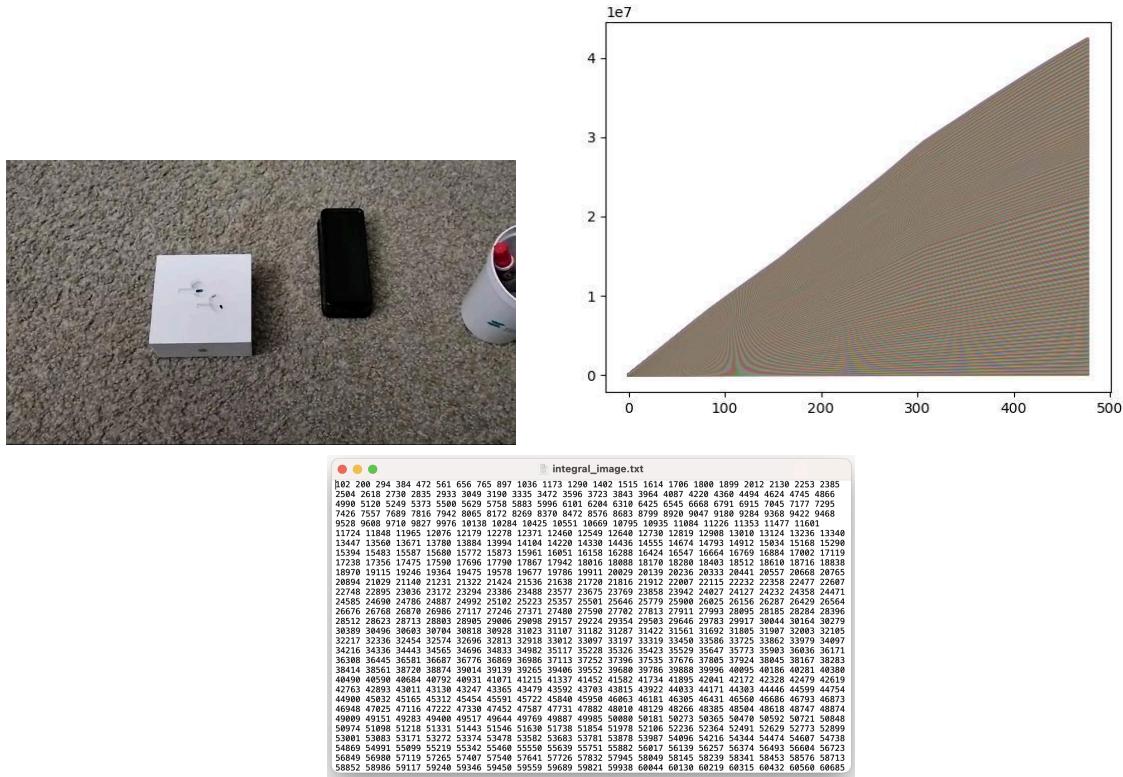
1. **Read RGB Frames:** Capture RGB frames from a camera or load a video file.
2. **Convert to Grayscale:** Convert each RGB frame to grayscale. Integral images are typically computed from grayscale images.
3. **Compute Integral Image:** For each grayscale frame, compute the integral image. The integral image at a pixel (x,y) contains the sum of all pixel values in the rectangle from (0,0) to (x,y). You can compute the integral image using the following formula:

$$\text{integral_image}(x,y) = \text{grayscale}(x,y) + \text{integral_image}(x-1,y) + \text{integral_image}(x,y-1) - \text{integral_image}(x-1,y-1)$$

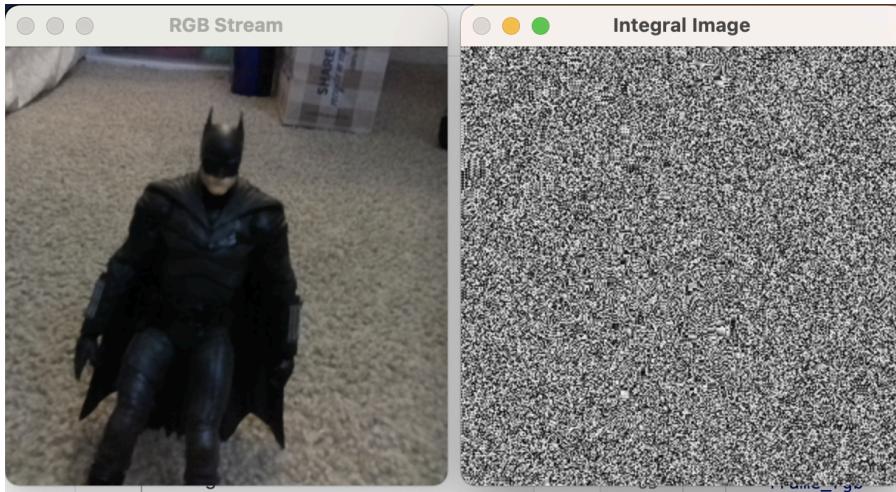
integral_image(x,y)=grayscale(x,y)+integral_image(x-1,y)+integral_image(x,y-1)-integral_image(x-1,y-1) Make sure to handle edge cases appropriately.

4. **Display Integral Image Feed:** Display the computed integral image feed along with the original RGB feed. You can use any suitable visualization method to display both feeds simultaneously, such as creating a split-screen display or overlaying the integral image on top of the RGB image.

For Image:



For Video Stream:



5. Implement the image stitching for a 360 degree panoramic output. This should function in real-time. You can use any type of features. You can use built-in libraries/tools provided by OpenCV or DepthAI API. You cannot use any built-in function that does `output = image_stitch(image1, image2)`. You are supposed to implement the `image_stitch()` function

Steps Involved:

1. Feature Detection and Matching:

- Detect keypoints and extract descriptors from each image. You can use feature detectors like SIFT, SURF, ORB, etc.
- Match keypoints between consecutive pairs of images. You can use feature matching algorithms like brute force matching, FLANN matching, etc.

2. Find Homography:

- Use the matched keypoints to estimate the homography transformation between consecutive pairs of images. The homography represents the perspective transformation between two images.
- Apply RANSAC (Random Sample Consensus) algorithm for robust estimation of the homography matrix.

3. Warp Images:

- Warp the second image (right image) onto the first image (left image) using the estimated homography matrix. This aligns the two images properly.

4. Blend Images:

- Blend the warped image with the first image to seamlessly merge them together. You can use techniques like feathering, alpha blending, etc., to avoid visible seams.

5. Repeat Steps for All Images:

- Repeat the above steps for all pairs of consecutive images until all images are stitched together.

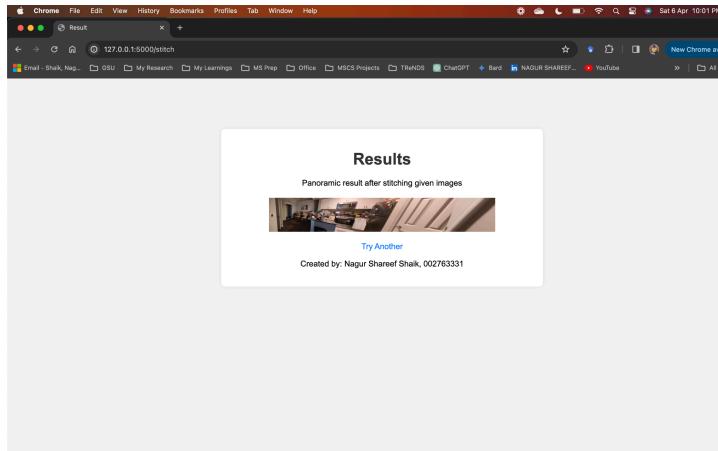
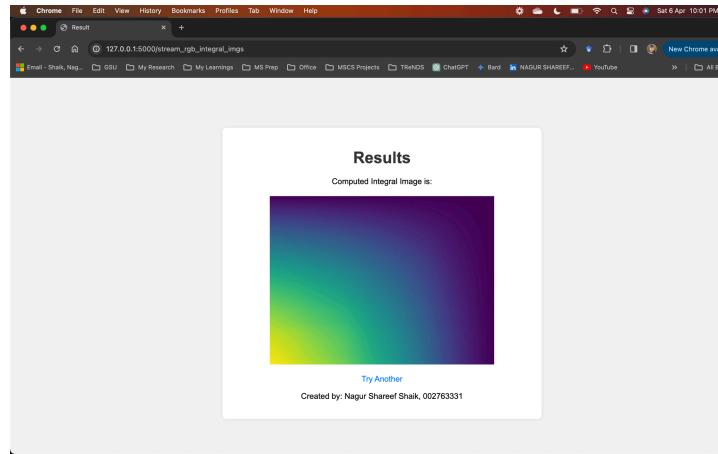
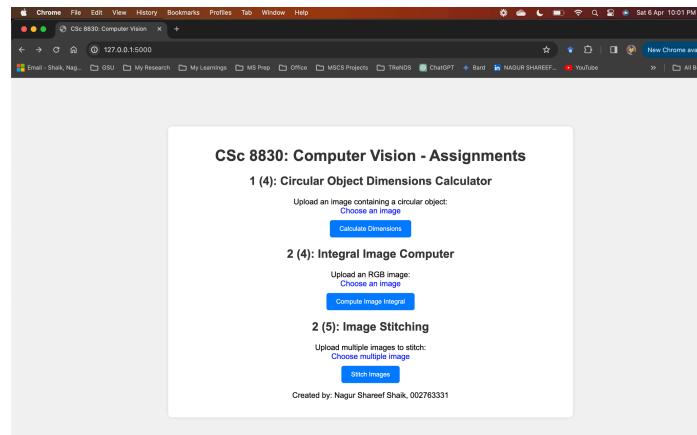
6. Finalize Panorama:

- Combine all the stitched images to create the final panorama. This can be achieved by blending overlapping regions and cropping the result to remove any black borders.

Stitched Image:



6. Integrate the applications developed for problems 4 and 5 with the web application developed in Assignment 1 problem 4*



Github Link:

<https://github.com/ShaikNagurShareef/CSc8830-Computer-Vision/tree/main/Assignment-2>