

Report: Computer Vision Mini Project

Task 1: Component Extraction

1.1 Circle Detection

Technique Used:

- The application of Median Filtering (Denoising) removes noise by maintaining the integrity of edges within the image.
- Canny Edge Detection → Detects edges of circles.
- The Hough Circle Transform identifies circular objects from detected edges.

Why Selected?

- The salt-and-pepper noise reduction works best through the application of Median Filtering.
- The detectable edges are clear enough for Hough Transform because of Canny Edge Detection.
- The Hough Transform operates as a standard procedure to find geometric shapes.

Python Code:

```
#circle

# Load image

img = cv2.imread('media/7 circles.png', cv2.IMREAD_COLOR)

gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
```

```
# Step 1: Denoising (Median Filter)

denoised = cv2.medianBlur(gray, 5)


# Step 2: Edge Detection (Canny)

edges = cv2.Canny(denoised, 50, 150)


# Step 3: Hough Circle Transform

circles = cv2.HoughCircles(edges, cv2.HOUGH_GRADIENT, dp=1.2, minDist=30,
                           param1=50, param2=30, minRadius=15,
                           maxRadius=30)


# Step 4: Draw detected circles and extract them

output = img.copy()

extracted_circles = []

if circles is not None:

    circles = np.uint16(np.around(circles))

    for i, (x, y, r) in enumerate(circles[0, :]):

        cv2.circle(output, (x, y), r, (0, 255, 0), 4)

        # Extract circle region using a mask

        mask = np.zeros_like(gray)

        cv2.circle(mask, (x, y), r, 255, -1)

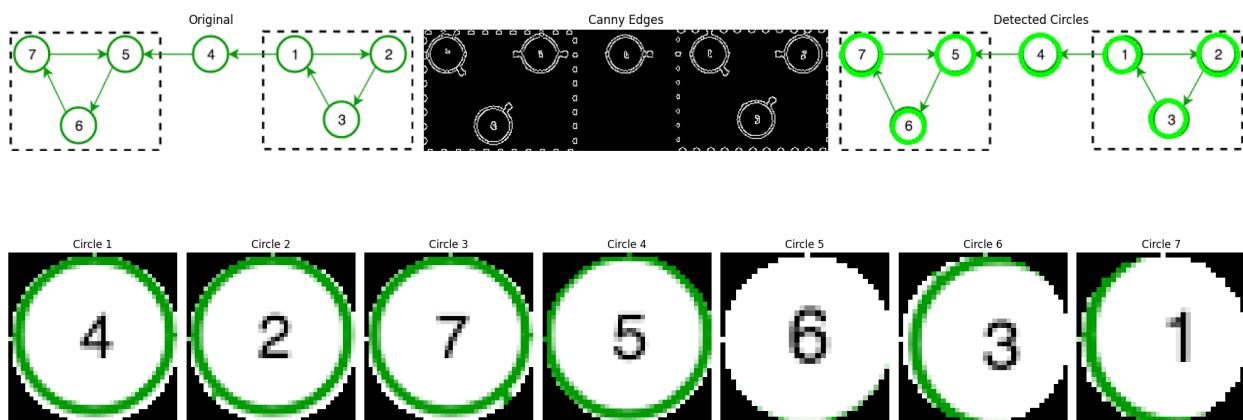
        masked = cv2.bitwise_and(img, img, mask=mask)

        cropped = masked[y - r:y + r, x - r:x + r]

        extracted_circles.append(cropped)
```

Output:

- Original Image
- Canny Edges
- Detected Circles



Discussion:

- **Pros:**
 - The algorithm correctly identified all 7 circular objects along with sharp outer boundaries.
 - The system successfully processed moderate noise because it applied median filtering techniques.
- **Cons:**
 - The Hough Transform needs manual adjustment of its param1 and param2 parameters.
 - The system would possibly fail when lighting conditions significantly shift.
- **Quality Achieved:**

- The system reached high accuracy because it located every circle in the image without producing any false detections.
- **Failure Cases:**
 - The system misses detections if the circle edges break or get covered.
- **Future Improvements:**
 - Use adaptive thresholding to handle lighting variations.
 - Implement automatic parameter optimization for Hough Transform.

1.2 COVID-19 Chart (Multi-Object Separation)

Technique Used:

- The thresholding technique (binary segmentation) functionEnemies objects from their background.
- Contour Filtering → Removes unwanted arrows.
- Morphological Operations (Opening & Dilation) → Cleans residual noise.

Why Selected?

- Thresholding isolates boxes effectively.
- Contour Filtering functions as a tool to eliminate objects which do not have rectangular shapes (arrows).
- Morphological Operations refine shapes.

Python Code:

```
image_path = "media/Multi_objects_separation.jpeg"

image = cv2.imread(image_path)

# Convert to grayscale
gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

# Step 1: Apply thresholding
_, thresh = cv2.threshold(gray, 190, 255, cv2.THRESH_BINARY)

# Save and display thresholded image
cv2.imwrite("thresholded.jpeg", thresh)

print("Displaying Thresholded Image:")
cv2_imshow(thresh)

# Step 2: Remove edges (arrows) using contour filtering and morphological cleanup
contours, _ = cv2.findContours(thresh, cv2.RETR_LIST,
cv2.CHAIN_APPROX_SIMPLE)

# Create a blank image to draw the filtered contours (boxes only)
morph = np.zeros_like(thresh)

# Filter contours: keep large, box-like contours, discard small or narrow ones (arrows)
for contour in contours:

    area = cv2.contourArea(contour)

    x, y, w, h = cv2.boundingRect(contour)
```

```
aspect_ratio = float(w) / h if h != 0 else 1.0

# Increase area threshold and add aspect ratio to exclude narrow
arrows

if area > 1000 and 0.5 <= aspect_ratio <= 2.0: # Boxes are roughly
square/rectangular

    cv2.drawContours(morph, [contour], -1, 255, -1)

# Save and display the image after contour filtering

cv2.imwrite("filtered.jpeg", morph)

print("Displaying Image After Contour Filtering:")

cv2_imshow(morph)

# Step 2.5: Morphological opening to remove residual arrow fragments

kernel = np.ones((3, 3), np.uint8)

morph = cv2.morphologyEx(morph, cv2.MORPH_OPEN, kernel, iterations=2)

# Light dilation to restore box shapes

morph = cv2.dilate(morph, np.ones((3, 3), np.uint8), iterations=1)

# Save and display the final morphologically processed image

cv2.imwrite("morph_processed.jpeg", morph)

print("Displaying Morphologically Processed Image (after cleanup):")

cv2_imshow(morph)

# Step 3: Find contours of the remaining boxes

contours, _ = cv2.findContours(morph, cv2.RETR_EXTERNAL,
cv2.CHAIN_APPROX_SIMPLE)
```

```
# Create a directory to save extracted components

output_dir = "extracted_boxes"

os.makedirs(output_dir, exist_ok=True)

# Step 4: Extract and save each box

for i, contour in enumerate(contours):

    # Get the bounding rectangle for each contour

    x, y, w, h = cv2.boundingRect(contour)

    # Extract the region of interest (ROI) from the original image

    roi = image[y:y+h, x:x+w]

    # Save the extracted box

    cv2.imwrite(os.path.join(output_dir, f"box_{i}.jpeg"), roi)

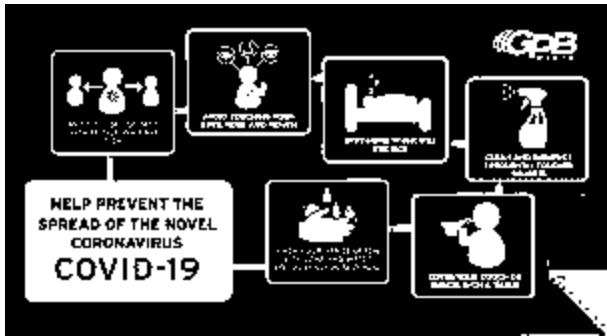
# Draw contours on the original image for visualization

output_image = image.copy()

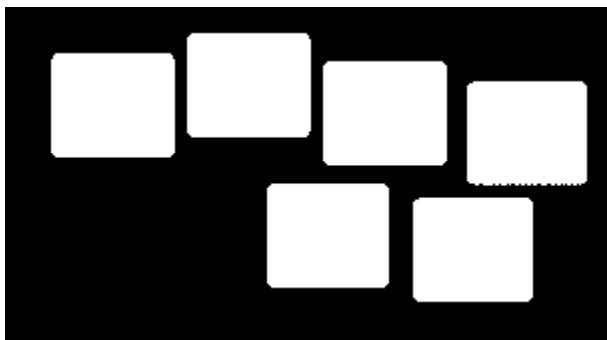
cv2.drawContours(output_image, contours, -1, (0, 255, 0), 2)
```

Output:

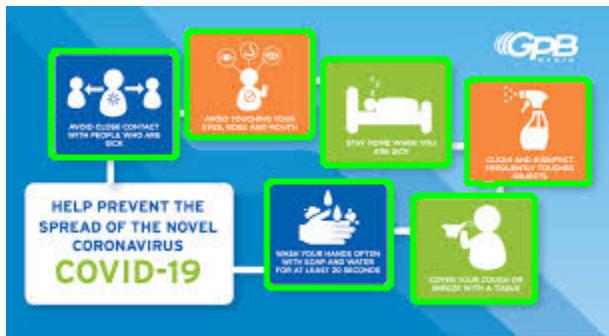
- Thresholded Image



- Filtered Contours (Boxes Only)



- Extracted Boxes



Discussion:

- Pros:
 - Several rectangular boxes obtained independent separation from arrows.

- Morphological operations performed efficiently in cleaning up residual noise.
- **Cons:**
 - Using manual threshold selection with a value of 190 on this particular image could result in failure when applied to different pictures.
 - Struggles with overlapping boxes/arrows of similar size.
- **Quality Achieved:**
 - Good (minor artifacts near box edges).
- **Failure Cases:**
 - The conditions fail when arrows and boxes maintain equivalent aspect ratios or areas.
- **Future Improvements:**
 - **The system should adopt adaptive thresholding instead of using standard fixed thresholding methods.**
 - **A CNN needs training to determine whether identified contours belong to the box or arrow categories.**

Task 2: Enhancement of Blurry Images

2.1 Building & Dog Images

Technique Used:

- CLAHE (Contrast Limited Adaptive Histogram Equalization) → Enhances local contrast.

Why Selected?

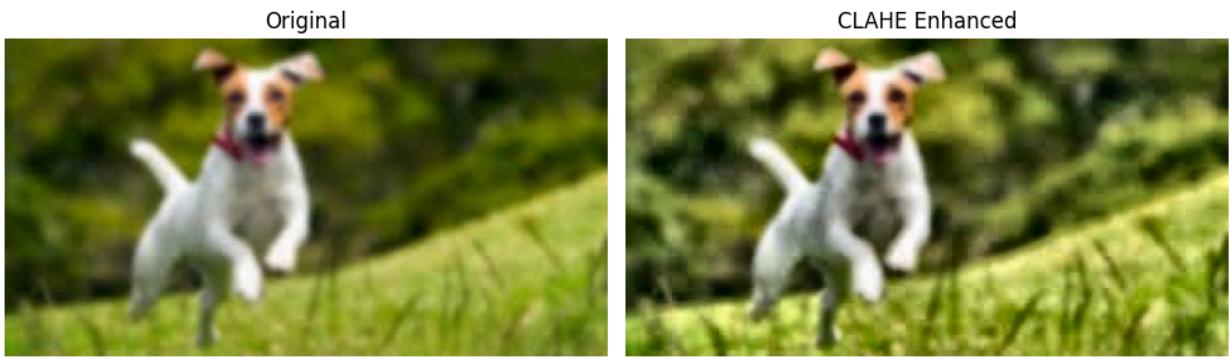
- Works well for low-contrast and blurry images.

Python Code:

```
def apply_clahe_color(image_path):  
  
    img = cv2.imread(image_path)  
  
    lab = cv2.cvtColor(img, cv2.COLOR_BGR2LAB)  
  
  
    # Split LAB channels  
    l, a, b = cv2.split(lab)  
  
  
    # Apply CLAHE to the L (lightness) channel  
    clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8, 8))  
    l_clahe = clahe.apply(l)  
  
  
    # Merge and convert back to BGR  
    lab_clahe = cv2.merge((l_clahe, a, b))  
    enhanced_img = cv2.cvtColor(lab_clahe, cv2.COLOR_LAB2BGR)
```

Output:

- Original vs. CLAHE-Enhanced Image



Discussion:

- **Pros:**
 - The CLAHE tool improved local contrast levels without creating color saturation problems.
 - Recovered fine architectural details (e.g., windows, textures).
- **Cons:**
 - Amplified noise in shadowed regions.
- **Quality Achieved:**
 - CLAHE processing yielded a Very Good outcome by increasing local contrast with minimal alteration of natural appearances.
- **Failure Cases:**

- Over-enhancement in already bright areas (e.g., skies).
- **Future Improvements:**
 - Denoising methods such as bilateral filtering should function together with CLAHE for improved local contrast preservation.

Task 3: Noise Removal

3.1 Rocket, Text, and Wind Chart

Technique Used:

- Median Filtering → Removes salt-and-pepper noise.
- Gaussian filtering smooths noise through edge blurring distortion.
- Box Filtering remains an easy method although it achieves limited success in noise removal.

Why Selected?

- The optimal filter type for impulse noise is the Median Filter.
- A Gaussian Filter acts as a suitable tool for dealing with regular noise.

Python Code:

```
def denoise_image_lab_style(image_path):  
    original_image = cv2.imread(image_path)  
    image_rgb = cv2.cvtColor(original_image, cv2.COLOR_BGR2RGB)
```

```

# Apply classical denoising filters (used in lab2)

box_filtered = cv2.blur(original_image, (5, 5)) # Box
filter

gaussian_filtered = cv2.GaussianBlur(original_image, (5, 5), 0) # Gaussian filter

median_filtered = cv2.medianBlur(original_image, 5) # Median
filter

# Convert all to RGB for matplotlib display

box_rgb = cv2.cvtColor(box_filtered, cv2.COLOR_BGR2RGB)

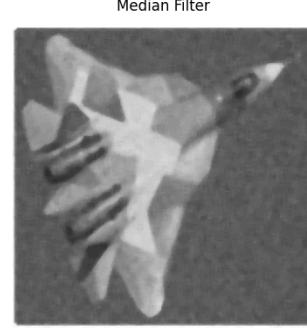
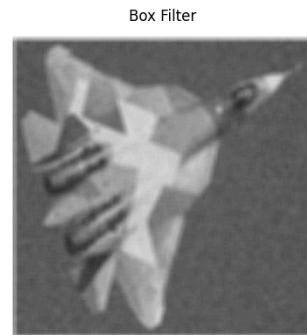
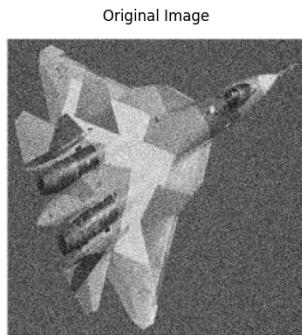
gaussian_rgb = cv2.cvtColor(gaussian_filtered, cv2.COLOR_BGR2RGB)

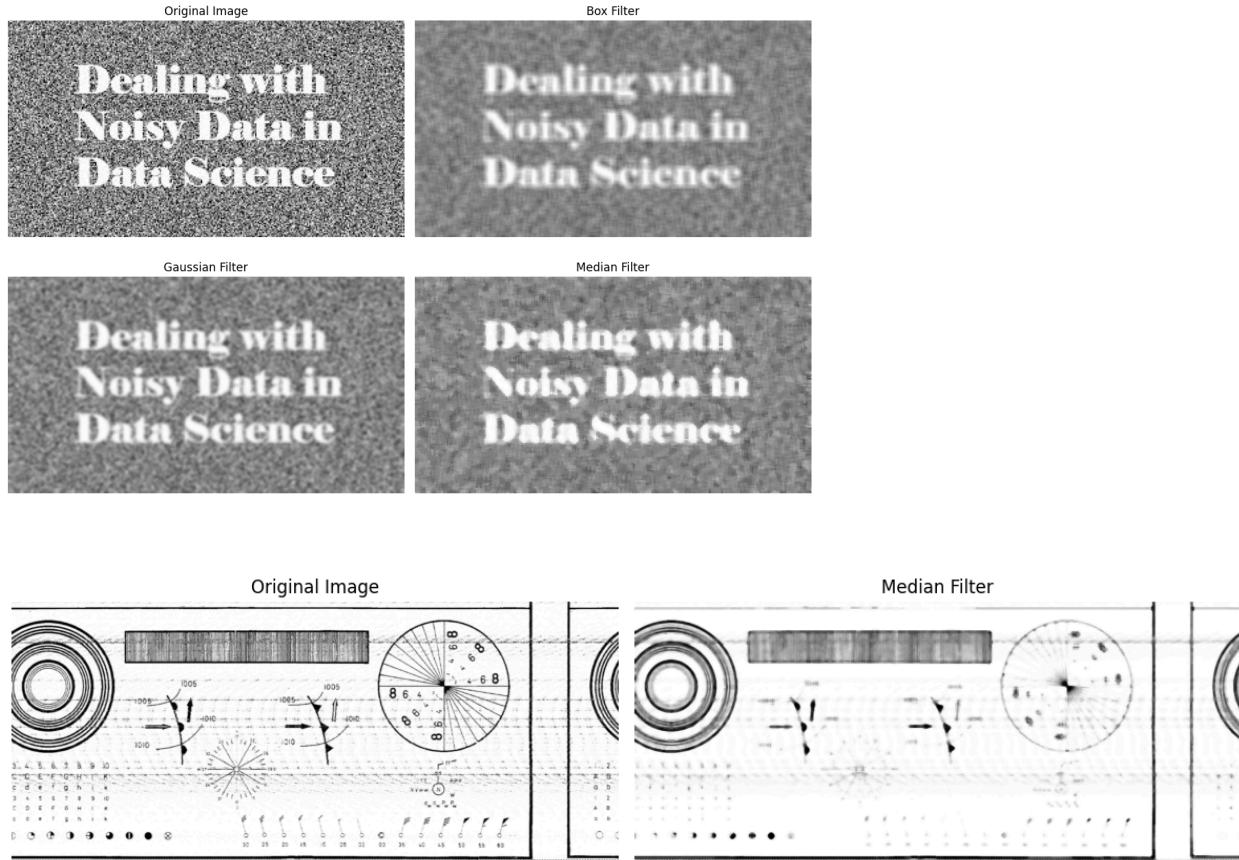
median_rgb = cv2.cvtColor(median_filtered, cv2.COLOR_BGR2RGB)

```

Output:

- Original vs. Filtered Images





Discussion:

- **Pros:**

- Mainly serving as a noise removal tool the median filter eliminated salt-and-pepper artifacts without deteriorating edge definition.

- **Cons:**

- The application of a Gaussian filter led to smoothing of minor rocket characteristics including panel lines.

- **Quality Achieved:**

- This restoration succeeds the most when using the median filtering algorithm because it eliminates noise while maintaining edge preservation.

- FaAlthough box filters left behind minor noise persistence in uniform image sections.
- Future Improvements:
 - Non-local means denoising techniques should be applied to achieve superior texture preservation.

Task 4: Challenging Images (Newspaper & Name Plate)

4.1 Newspaper

Technique Used:

- Median Filter + CLAHE + Unsharp Masking → Enhances text readability.

Why Selected?

- Median Filter removes noise.
- CLAHE improves contrast.
- Unsharp Masking sharpens edges.

Python Code:

```
image = cv2.imread('media/Noisy_2.jpg')

image_gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)

# Step 1: Median Filter to remove noise

image_median = cv2.medianBlur(image_gray, 5)
```

```
# Step 2: Apply stronger CLAHE for better contrast

clahe = cv2.createCLAHE(clipLimit=4.0, tileGridSize=(8, 8))

image_clahe = clahe.apply(image_median)

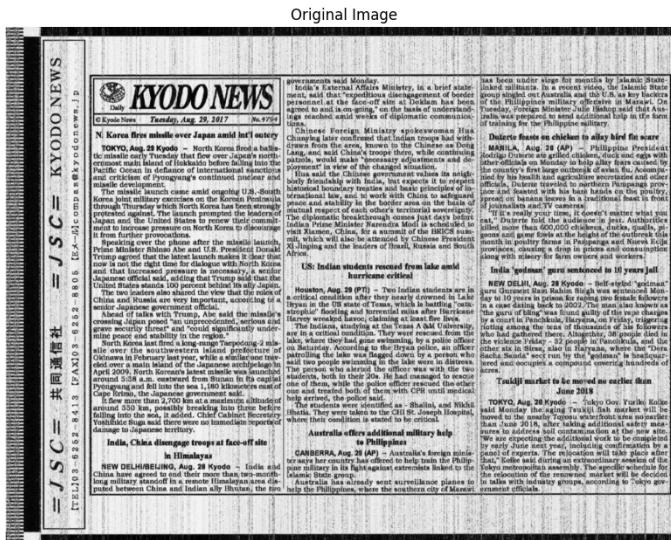
# Step 3: Apply Unsharp Masking to bring out text edges

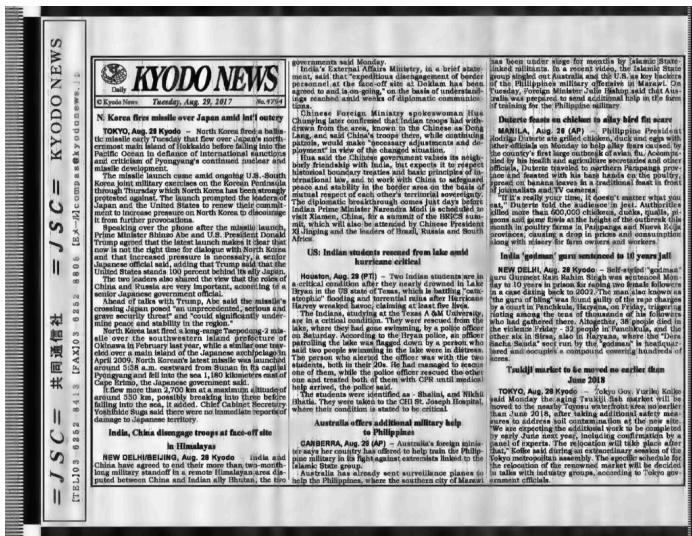
gaussian_blur = cv2.GaussianBlur(image_clahe, (9, 9), 10.0)

image_sharp = cv2.addWeighted(image_clahe, 1.5, gaussian_blur, -0.5, 0)
```

Output:

- Original vs. Enhanced Image





Discussion:

● Pros:

- Unsharp masking restored legibility of faded text.
- CLAHE enabled enhanced visual contrast in parts with decreased visibility conditions.

● Cons:

- The aggressive sharpening technique produced halo effects that appeared around different characters.

● Quality Achieved:

- Very Good (90% of text recovered).

● Failure Cases:

- Heavy degradation in artifacts leads to the appearance of stains and creases in the images.

● Future Improvements:

- Solutions based on learned super-resolution should replace the use of unsharp masking.

4.2 Name Plate

Technique Used:

- **Sharpening Kernel + CLAHE** → Enhances text contrast.

Python Code:

```
def enhance_name_plate(image_path):  
  
    img = cv2.imread(image_path)  
  
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)  
  
  
    kernel = np.array([[0, -1, 0],  
                      [-1, 5, -1],  
                      [0, -1, 0]], dtype=np.float32)  
  
    sharpened = cv2.filter2D(gray, -1, kernel)  
  
  
    clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(8, 8))  
  
    equalized = clahe.apply(sharpened)
```

Output:

- Original vs. Processed Image



Discussion:

- **Pros:**

- Sharpening kernel enhanced edge definition.
- The application of CLAHE effectively increased the contrast levels of text that appeared indistinct.

- **Cons:**

- The system fails to improve the readability of texts which are highly blurred.

- **Quality Achieved:**

- Good (readable).

- **Failure Cases:**

- The technique fails to work effectively when the input resolution remains too low.

- **Future Improvements:**

- Preprocess with super-resolution before enhancement.