

CRISP—CONTENT-BASED-RAPID-IMAGE-SEACH-USING-PARALLEL-COMPUTING

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Project Explanation: Content-Based Image Retrieval (CBIR) with Sequential and Parallel Processing

This project implements a **Content-Based Image Retrieval (CBIR) system**, which searches for similar images based on their visual features rather than metadata (like filenames or descriptions). The system extracts features from images and compares them using the **Chi-Square Distance** metric. Additionally, it compares **sequential processing** with **parallel processing** to evaluate speedup.

Key Components:

1. Image Preprocessing (preprocess_image(image_path))

- Reads an image using OpenCV.
- Resizes it to **500x500** for consistency.

```
# Resize the image
if original_image is not None:
    resized_image = cv2.resize(original_image, (500, 500))
    rgb_original = cv2.cvtColor(original_image, cv2.COLOR_BGR2RGB)
    rgb_resized = cv2.cvtColor(resized_image, cv2.COLOR_BGR2RGB)
    print("\nInput vs Output:")
    display("Original Image", rgb_original, "Resized Image", rgb_resized)
```

Python

Input vs Output:



- Converts it to **grayscale**.

```
# Convert the resized image to grayscale
if 'resized_image' in locals():
    gray_image = cv2.cvtColor(resized_image, cv2.COLOR_BGR2GRAY)
    rgb_resized = cv2.cvtColor(resized_image, cv2.COLOR_BGR2RGB)
    print("\nInput vs Output:")
    display("Resized Image", rgb_resized, "Grayscale Image", gray_image, cmap_out='gray')
```

Python

Input vs Output:

Resized Image



Grayscale Image



- Applies **Gaussian Blur** to remove noise.

```
# Apply Gaussian blur to the grayscale image
if 'gray_image' in locals():
    blurred_image = cv2.GaussianBlur(gray_image, (5, 5), 0)
    print("\nInput vs Output:")
    display("Grayscale Image", gray_image, "Blurred Image", blurred_image, cmap_in='gray', cmap_out='gray')
```

Python

Input vs Output:

Grayscale Image



Blurred Image

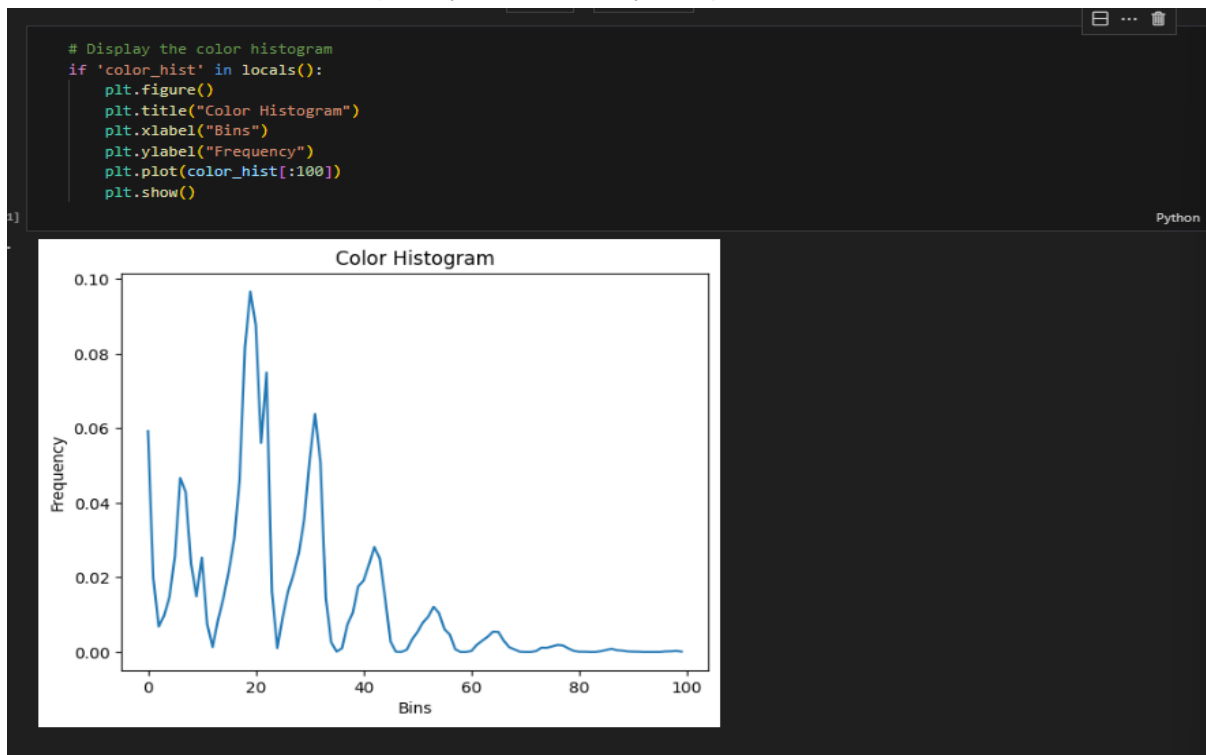


- Enhances edges using **Laplacian sharpening**.



2. Feature Extraction (`extract_features(image)`)

- Extracts a **color histogram** (12x12x12 bins) to capture color distribution.



```
# Extract the color histogram (no direct image output)
if 'resized_image' in locals():
    def extract_color_histogram(image, bins=(12, 12, 12)):
        hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
        hist = cv2.calcHist([hsv], [0, 1, 2], None, bins, [0, 180, 0, 256, 0, 256])
        cv2.normalize(hist, hist)
        return hist.flatten()

    color_hist = extract_color_histogram(resized_image)
    rgb_resized = cv2.cvtColor(resized_image, cv2.COLOR_BGR2RGB)
```

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- Computes **Hu Moments**, which help describe the shape of objects in an image.

```
# Extract Hu Moments
if 'gray_image' in locals():
    def extract_hu_moments(image):
        moments = cv2.moments(image)
        hu_moments = cv2.HuMoments(moments).flatten()
        return -np.sign(hu_moments) * np.log10(np.abs(hu_moments))

    hu_moments = extract_hu_moments(gray_image)
    print("\nOutput: Hu Moments:", hu_moments)
```

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...

Output: Hu Moments: [2.88156247 8.43503971 10.29492196 11.05178905 21.95152247 15.34317623 21.81954781]

3. Similarity Measurement (*chi2(histA, histB)*)

- Uses the **Chi-Square Distance** to compare two feature vectors.
- A smaller distance means the images are more similar.
- **Lower Chi-Square score (closer to 0):** The images are **more similar**.
- **Higher Chi-Square score:** The images are **less similar**.

```
# Chi-Square Distance Function
def chi2(histA, histB, eps=1e-10):
    return 0.5 * np.sum(((histA - histB) ** 2) / (histA + histB + eps))
```

1 Python


Implementation of CBIR in Two Approaches

1. Sequential Processing





- Reads all images one by one and extracts features.
- Computes distances between the query image and all dataset images.
- Sorts and returns the **top 5 most similar images**.

Sequential CBIR Time: 155.34 seconds

Query Image

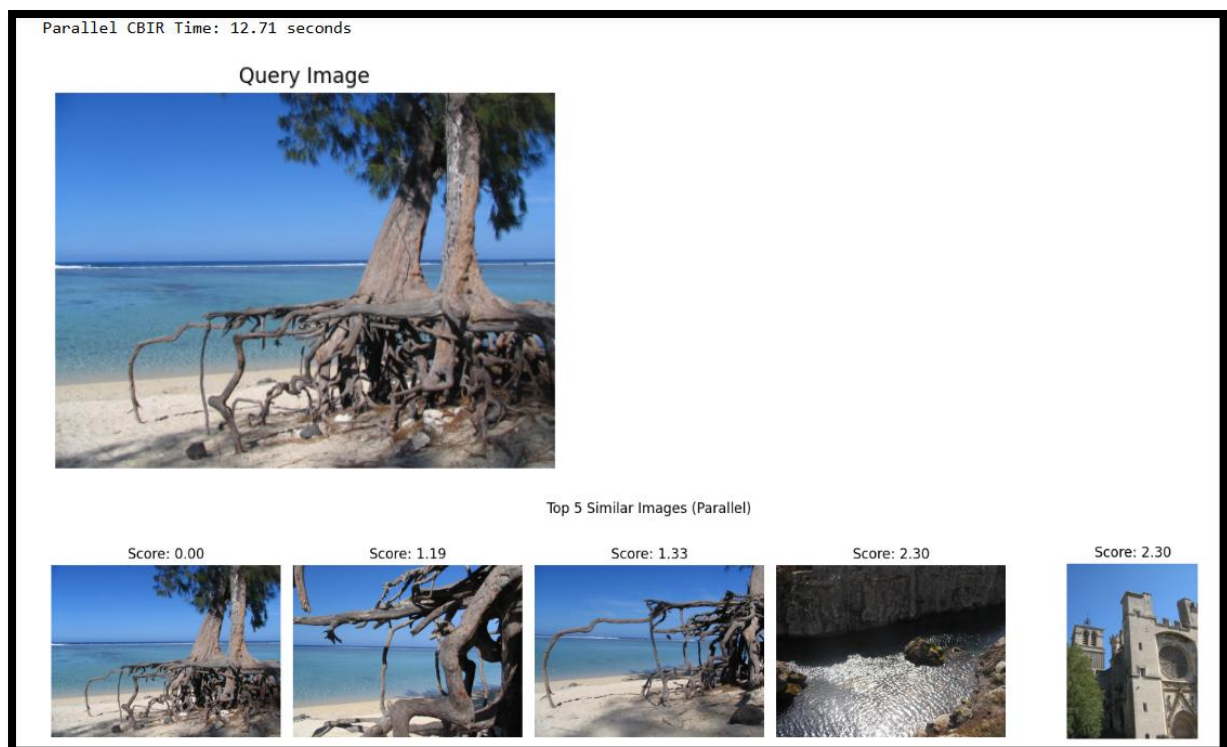


Top 5 Similar Images (Sequential)

Score: 0.00	Score: 1.19	Score: 1.33	Score: 2.30	Score: 2.30
				

2. Parallel Processing (Using ThreadPoolExecutor)

- Uses **multithreading** to extract features from multiple images simultaneously.
- Computes similarity distances in parallel.
- This improves speed compared to the sequential approach.



Performance Comparison

- Measures the execution time for **both sequential and parallel approaches**.
- **Speedup** is calculated as: $\text{Speedup} = \frac{\text{Sequential Execution Time}}{\text{Parallel Execution Time}}$
- A higher speedup means parallel processing is more efficient.

```
### Speedup Calculation ###  
speedup = seq_time / par_time  
print(f"Speedup: {speedup:.2f}x")
```

Python

Speedup: 12.22x

Visualization

- Displays the **query image**.
- Shows the **top 5 retrieved similar images** for both **sequential and parallel** approaches.

- *Each retrieved image is displayed with its similarity score.*
-

Conclusion

- *The project **demonstrates the efficiency of parallel computing** in image retrieval tasks.*
- ***Parallel processing significantly reduces computation time**, making CBIR systems more scalable.*
- *This can be extended to **large-scale image databases** for applications like **image search engines, medical imaging, and facial recognition**.*

CODE:

https://drive.google.com/file/d/1Z0LtyceDtrMBtlarhQvuLE9TTl5fh0gq/view?usp=drive_link

DATASET:

<https://www.kaggle.com/datasets/vadimshabashov/inria-holidays>