

# Image Enhancement In Frequency Domain Using Gaussian Filter

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# Project Objective

1

**Improve image  
quality**

Through Unsharp  
Masking



2

**Improve  
performance**

Through applying  
parallel computing

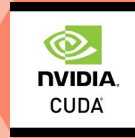


# Platforms Used



## Open MP

C++, run using Visual Studio 2022, for parallel computing



## CUDA

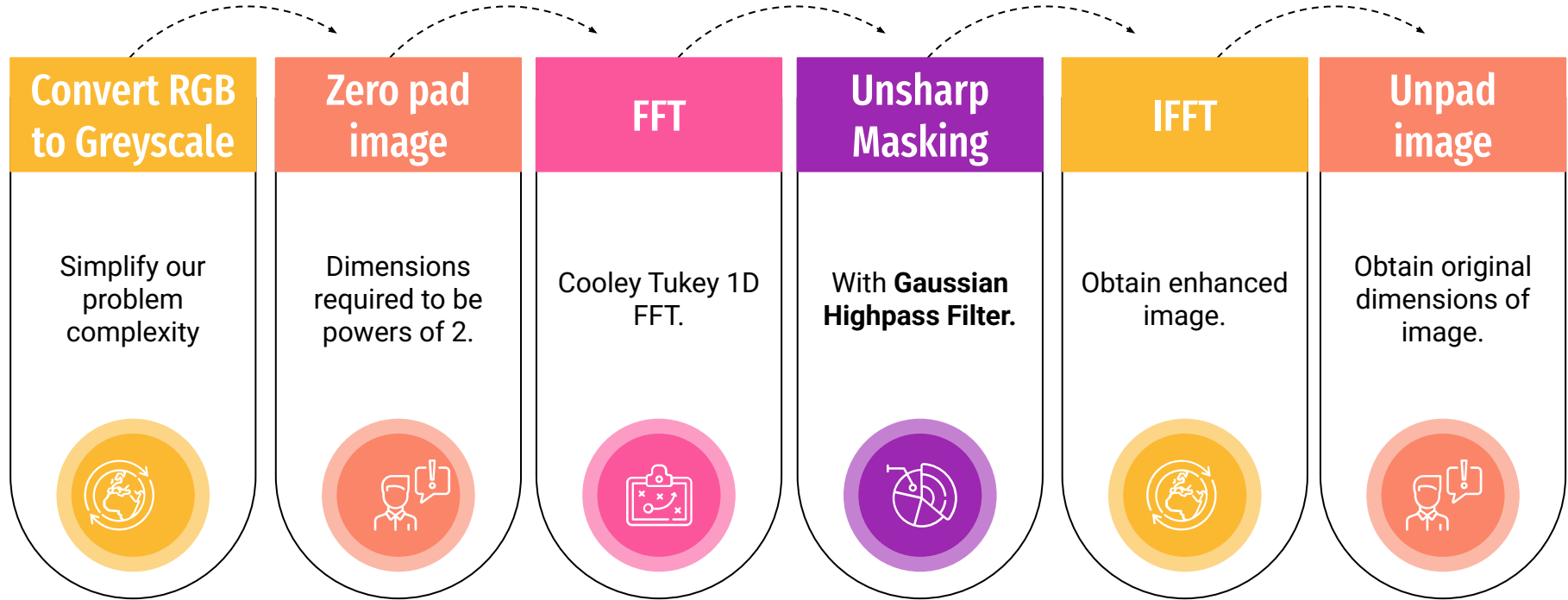
C++, run using Visual Studio 2022, for parallel computing



## Seaborn, Matplotlib

Python, run using script and ipykernel

# General process flow



# Areas to be parallelized

FFT



## Reason

Possible to be broken down into smaller independent sub problems.

Gaussian Highpass Filter



## Reason

Compute and apply filter are both Independent operations

IFFT



## Reason

Same reason as FFT

# Recursive 1D FFT using Cooley Tukey Algorithm (splitting step)

$[0, 1, 2, 3, 4, 5, 6, 7]$

even indexes

$[0, 2, 4, 6]$

odd indexes

$[1, 3, 5, 7]$

even indexes

$[0, 4]$

odd indexes

$[2, 6]$

even indexes

$[1, 5]$

odd indexes

$[3, 7]$

even indexes

$[0]$

odd indexes

$[4]$

even indexes

$[2]$

odd indexes

$[6]$

even indexes

$[1]$

odd indexes

$[5]$

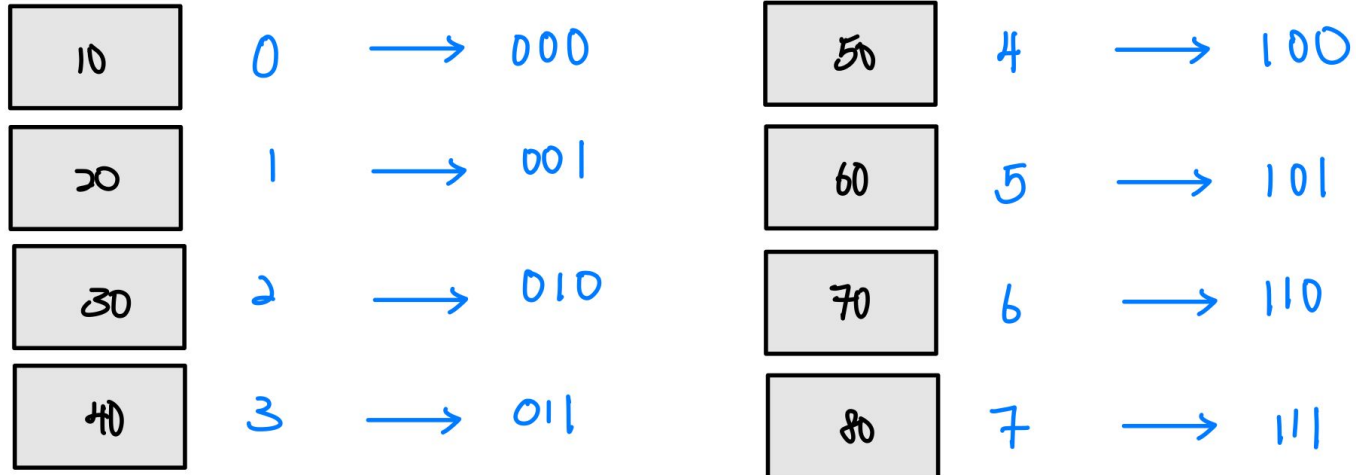
even indexes

$[3]$

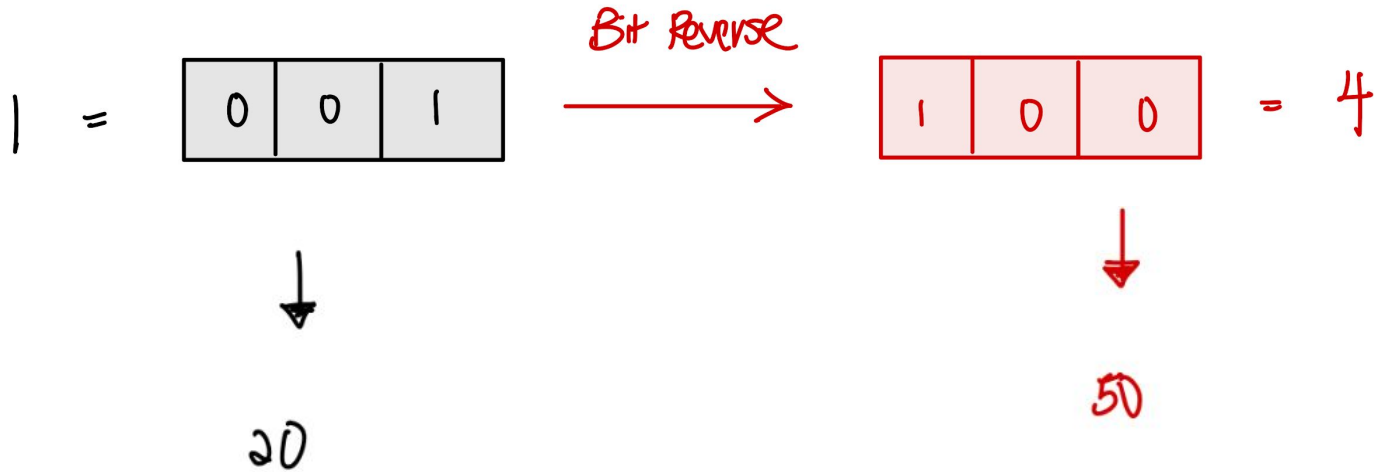
odd indexes

$[7]$

# Iterative 1D FFT using Cooley Tukey Algorithm



# Iterative FFT using Cooley Tukey Algorithm





# Iterative FFT using Cooley Tukey Algorithm



# Iterative & Recursive Splitting Final Result

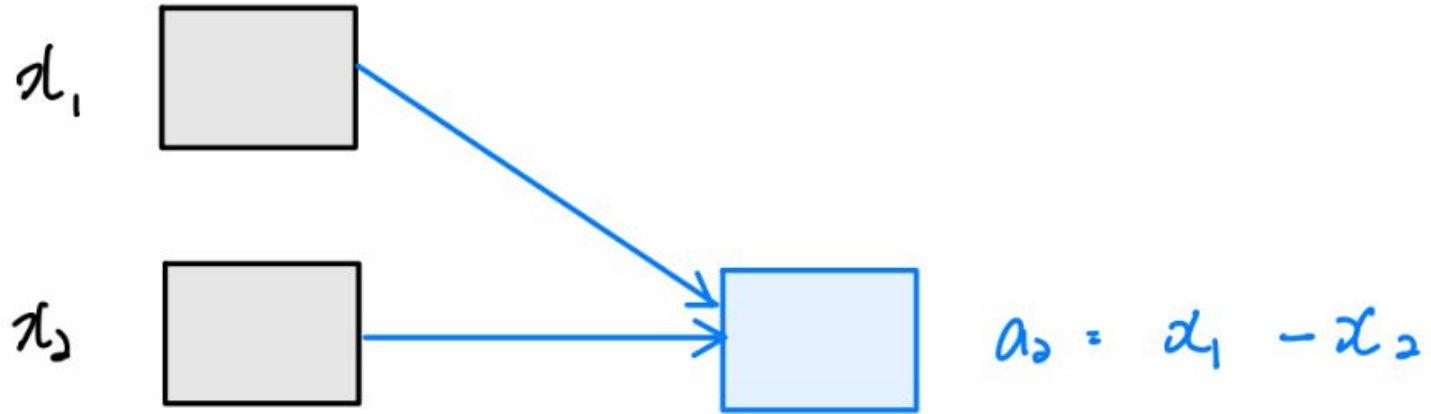
Iterative Final Result :

10	50	30	70	20	60	40	80
0	4	2	6	1	5	3	7

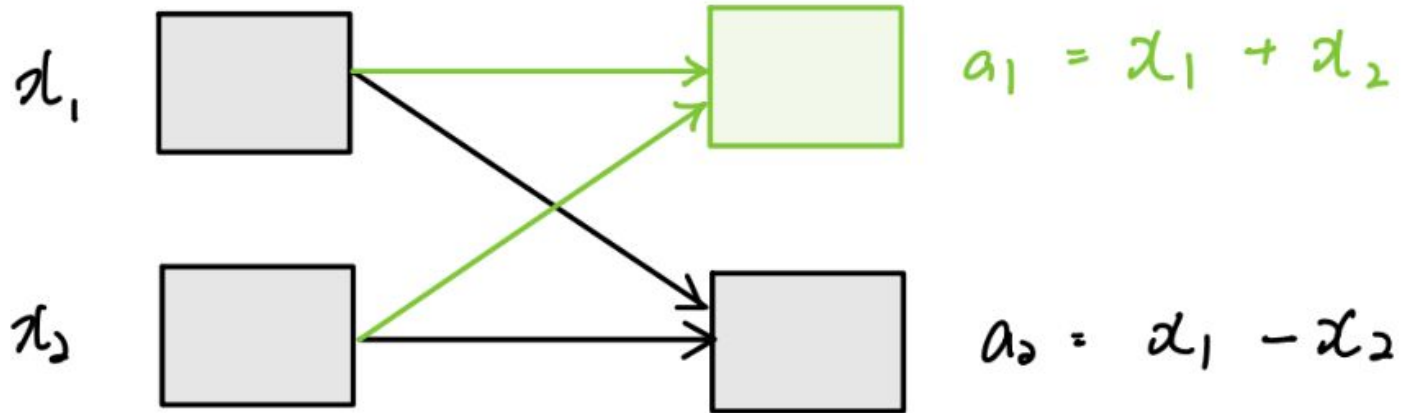
Recursive Final Result :

even indexes ↙	↓ indexes	even indexes ↙	↓ indexes	odd indexes ↙	indexes ↙	↓ indexes	indexes ↙	↓ indexes
[0]	[4]	[2]	[6]	[1]	[5]	[3]	[7]	

## Combination Step : Twiddle Factor



## Combination Step : Twiddle Factor

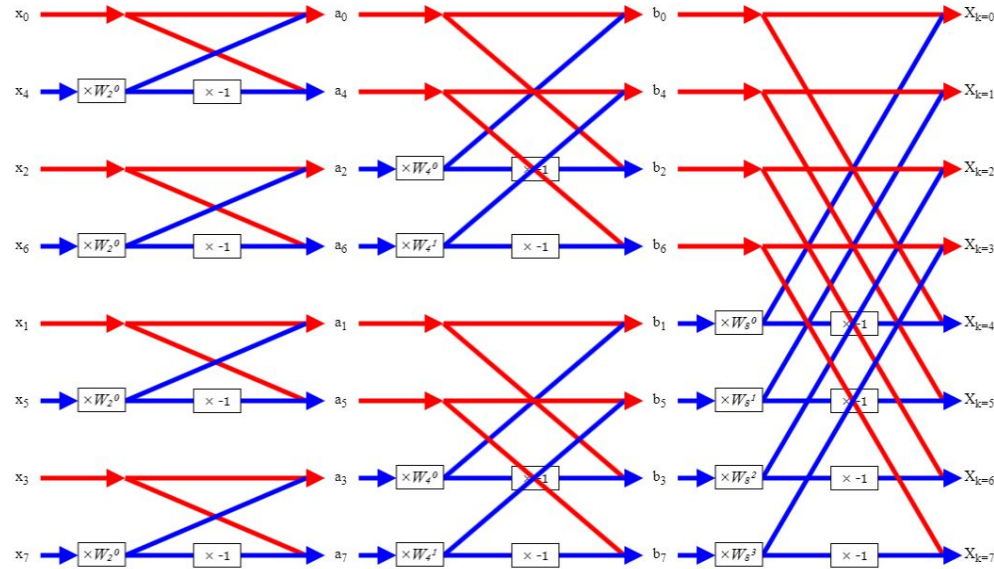


## Combination Step : Twiddle Factor

$$W_N^k = e^{\frac{-j2\pi k}{N}}$$

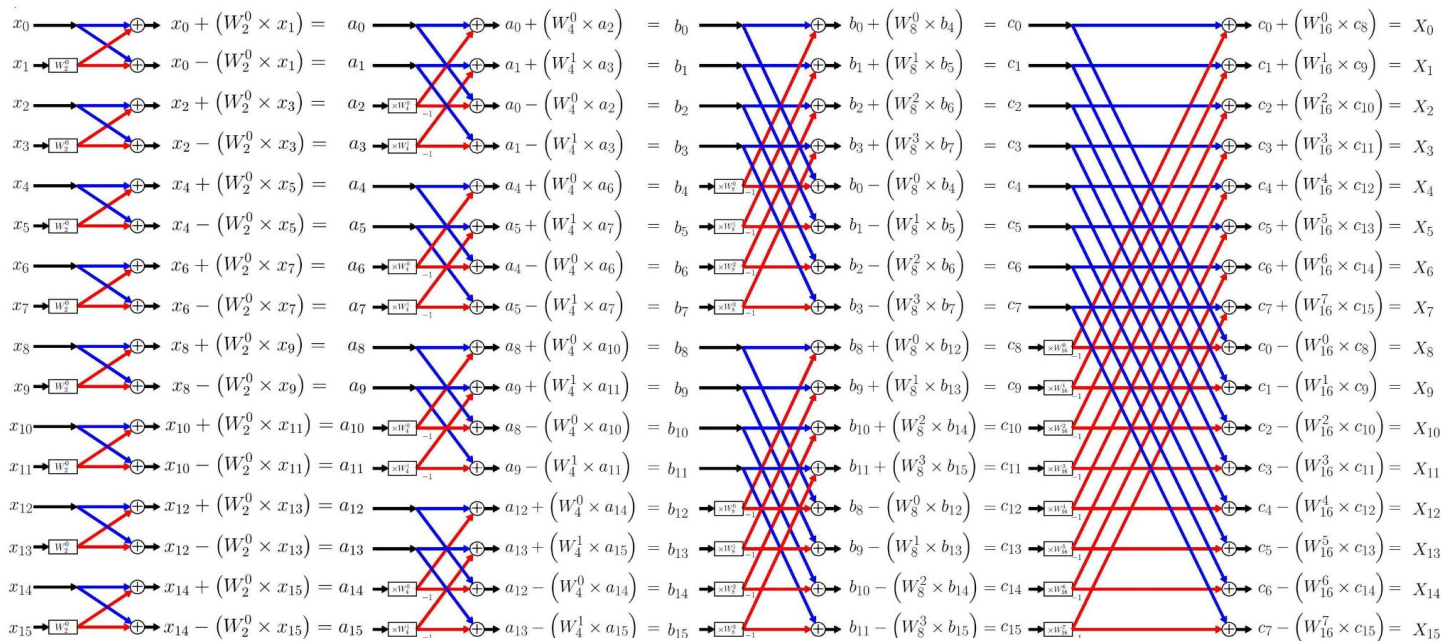
$$W_N^k = \cos\left(2\pi \times \frac{k}{N}\right) - j \sin\left(2\pi \times \frac{k}{N}\right)$$

# WHY Parallel FFT



$$8 \times \log_2(8) = 24$$

# WHY Parallel FFT



$$16 \times \log_2(16) = 64$$

# Gaussian High Pass Filter



Fig. 3: original image



Fig. 5: Gaussian high pass filter

The Gaussian high pass filter is given as:

$$H(u, v) = 1 - e^{-D^2(u, v) / 2D_0^2}$$

The formula for applying a **Gaussian High-Pass Filter** is:

$$G_{\text{highpass}}(u, v) = F(u, v) \cdot H(u, v)$$

The cutoff frequency ( $D_0$ ) controls which frequencies are filtered: lower  $D_0$  blurs more, while higher  $D_0$  sharpens details.



# Unsharp Masking using Gaussian Highpass Filter



Original Image



Unsharp Masking

$$G_{\text{sharpened}}(x, y) = G(x, y) + \alpha \cdot G_{\text{highpass}}(x, y)$$

$\alpha$ : The scaling factor controlling the intensity of sharpening ( $\alpha > 0$ ).

## The Different Between FFT & IFFT

$$F(u, v) = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} A(x, y) e^{-j2\pi \left( \frac{ux}{N} + \frac{vy}{M} \right)}$$

$$A(x, y) = \frac{1}{NM} \sum_{u=0}^{N-1} \sum_{v=0}^{M-1} F(u, v) e^{j2\pi \left( \frac{ux}{N} + \frac{vy}{M} \right)}$$

# WHY Normalize

Original

$$\begin{bmatrix} 1 & 2 & 3 & 4 \\ 5 & 6 & 7 & 8 \\ 9 & 10 & 11 & 12 \\ 13 & 14 & 15 & 16 \end{bmatrix}$$

After FFT

$$\begin{bmatrix} 136 + 0j & -8 + 8j & -8 + 0j & -8 - 8j \\ -32 + 32j & 0 + 0j & 0 + 0j & 0 + 0j \\ -32 + 0j & 0 + 0j & 0 + 0j & 0 + 0j \\ -32 - 32j & 0 + 0j & 0 + 0j & 0 + 0j \end{bmatrix}$$

# WHY Normalize

After IFFT

$$\begin{bmatrix} 16 + 0j & 32 + 0j & 48 + 0j & 64 + 0j \\ 80 + 0j & 96 + 0j & 112 + 0j & 128 + 0j \\ 144 + 0j & 160 + 0j & 176 + 0j & 192 + 0j \\ 208 + 0j & 224 + 0j & 240 + 0j & 256 + 0j \end{bmatrix}$$

# Result - Grayscale

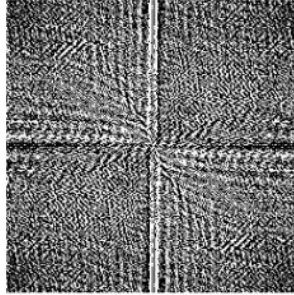
Original



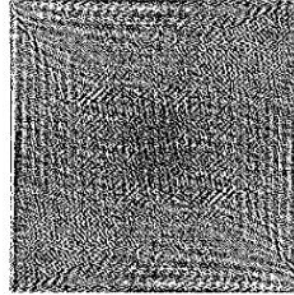
Grayscale



Frequency Domain



Gaussian Filter



Spatial Domain



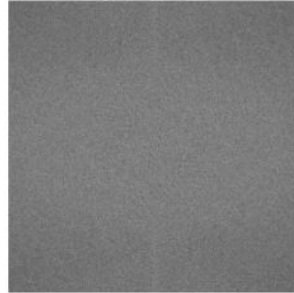
Original



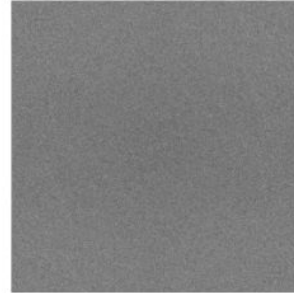
Grayscale



Frequency Domain



Gaussian Filter



Spatial Domain



# Result - Grayscale ( Before & After )

Before



After





# Result - Grayscale ( Before & After )

Before



After



# Result - Grayscale ( Before & After )

Original



Applied once





# Result - Grayscale ( Before & After )

Original

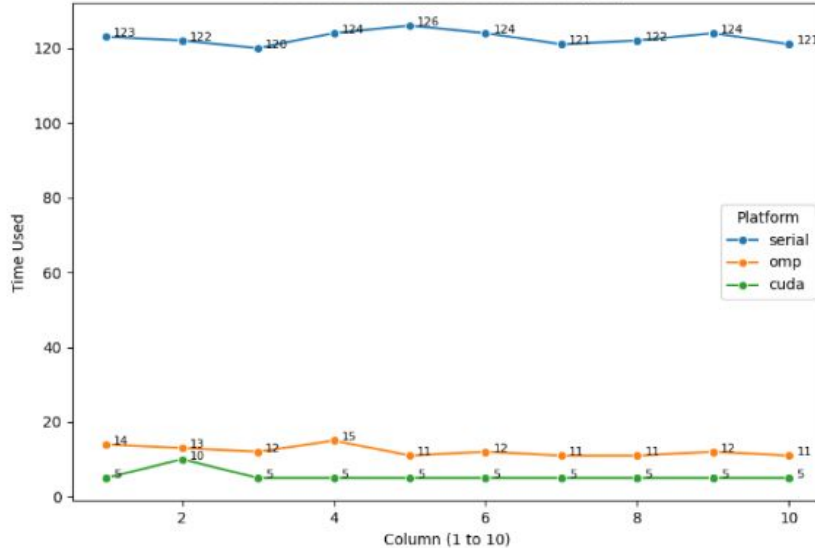


Applied four times

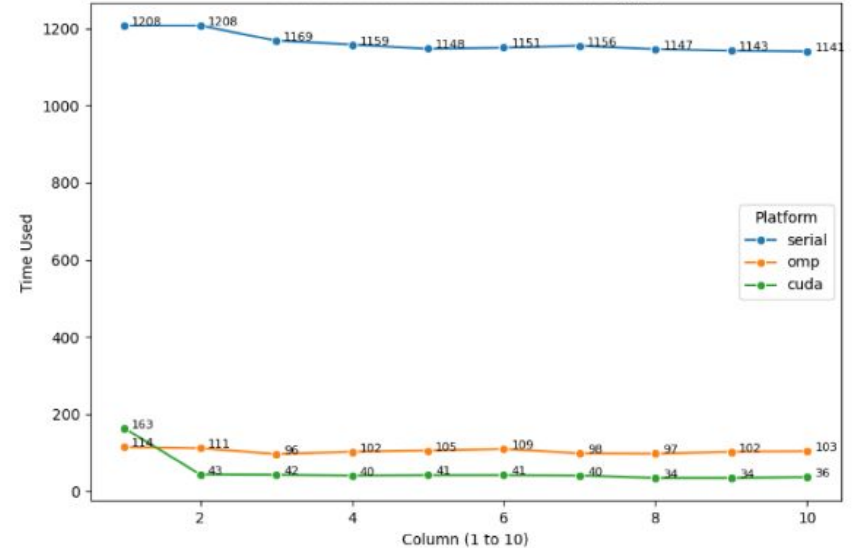


# Result - Grayscale (Runtimes)

Serial vs. OMP vs. CUDA Runtimes (lena)



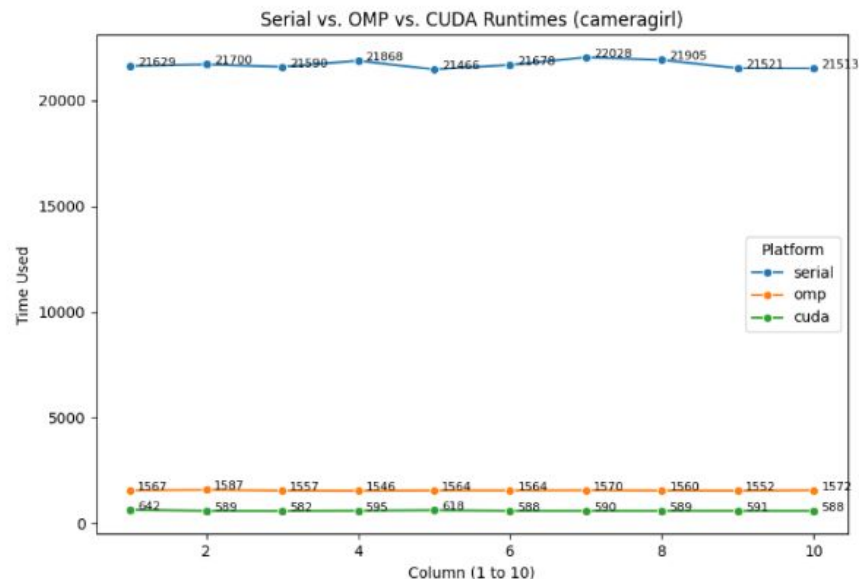
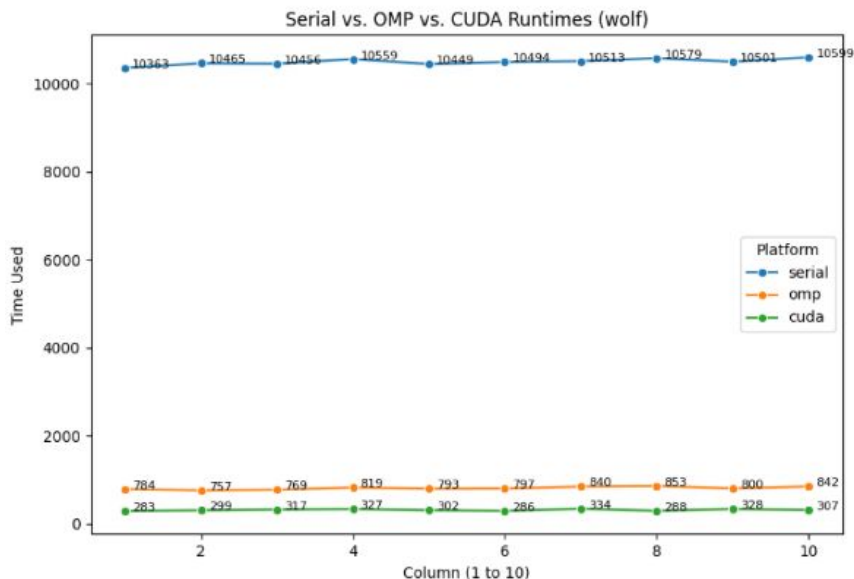
Serial vs. OMP vs. CUDA Runtimes (doggo)



Threads used for OMP: 16

Threads per block used for CUDA: 256

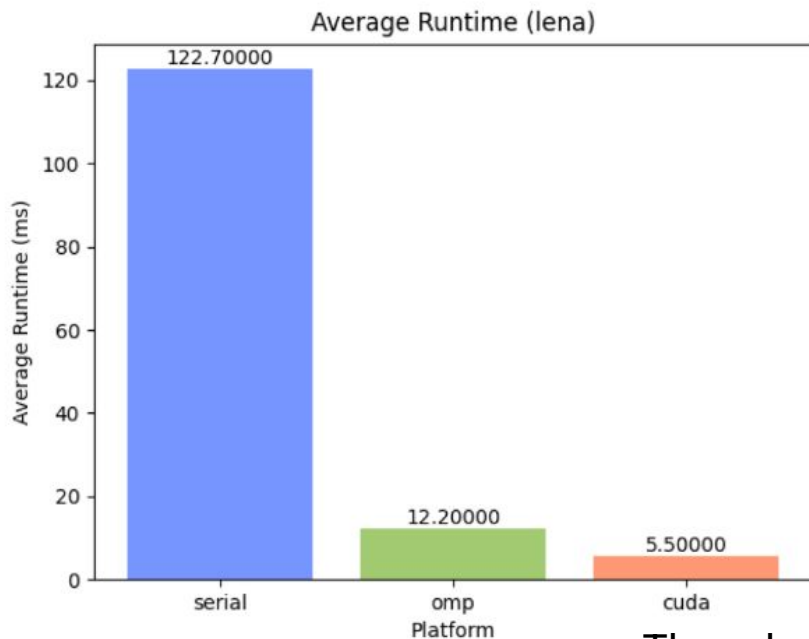
# Result - Grayscale (Runtimes)



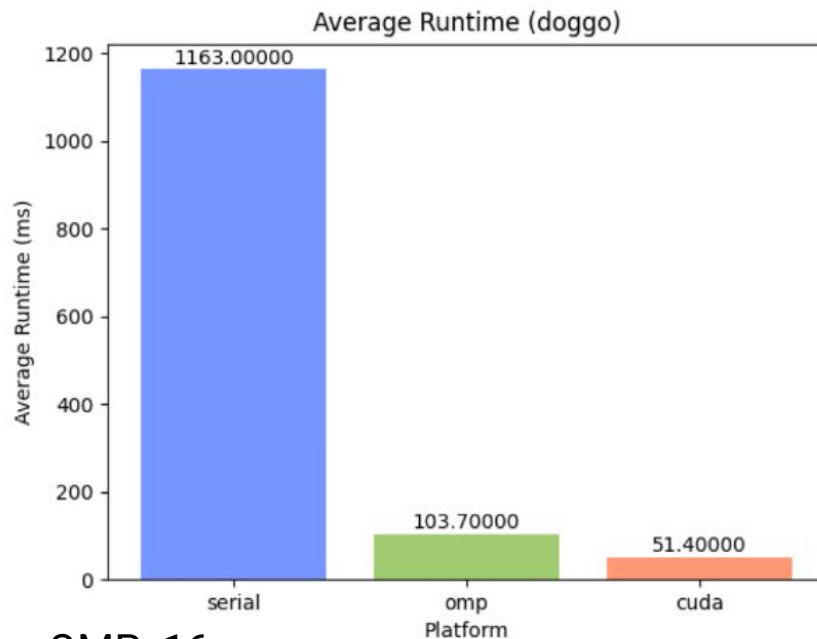
Threads used for OMP: 16  
Threads per block used for CUDA: 256

# Result - Grayscale (Average Runtimes)

Dimensions : 256 x 256, Size : 28.6 KB



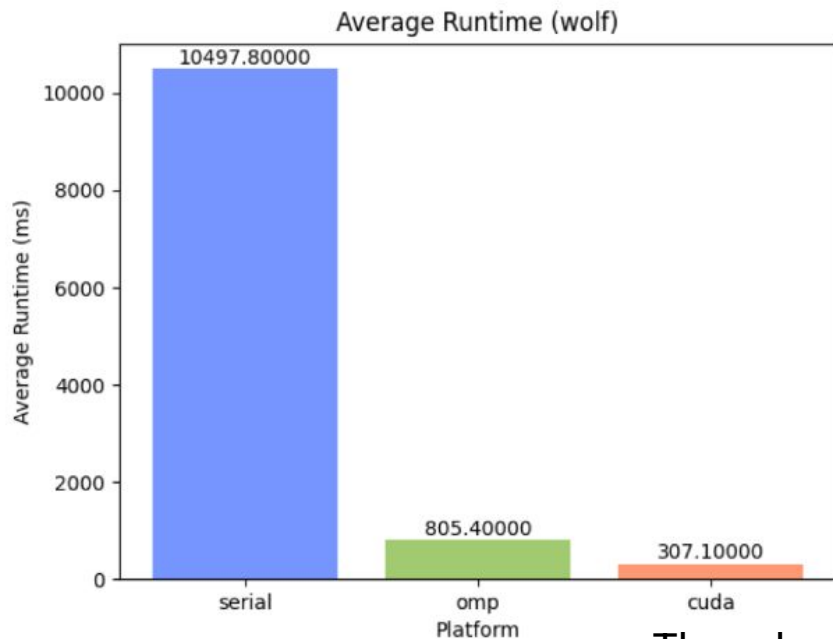
Dimensions : 678 x 446, Size : 12.7 KB



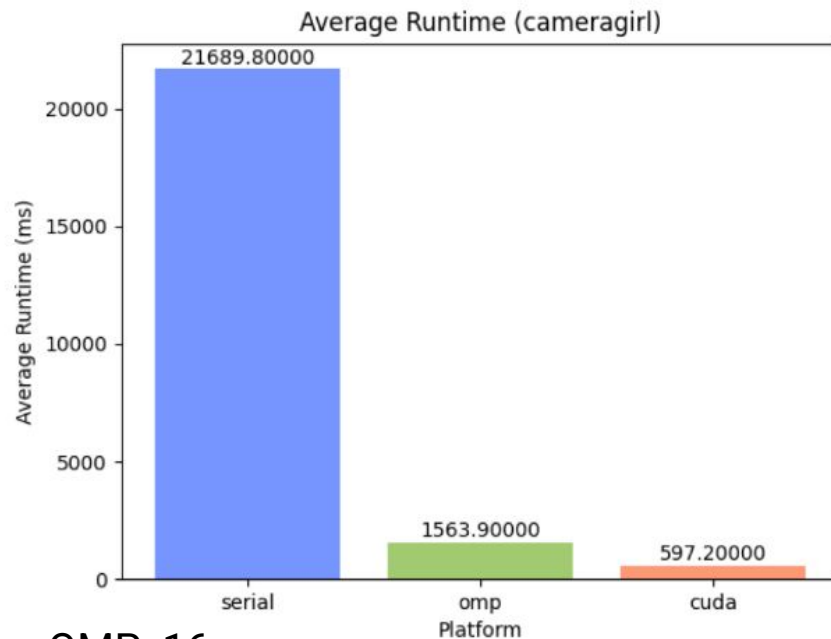
Threads used for OMP: 16  
Threads per block used for CUDA: 256

# Result - Grayscale (Average Runtimes)

Dimensions : 2048 x 2048, Size : 1 MB

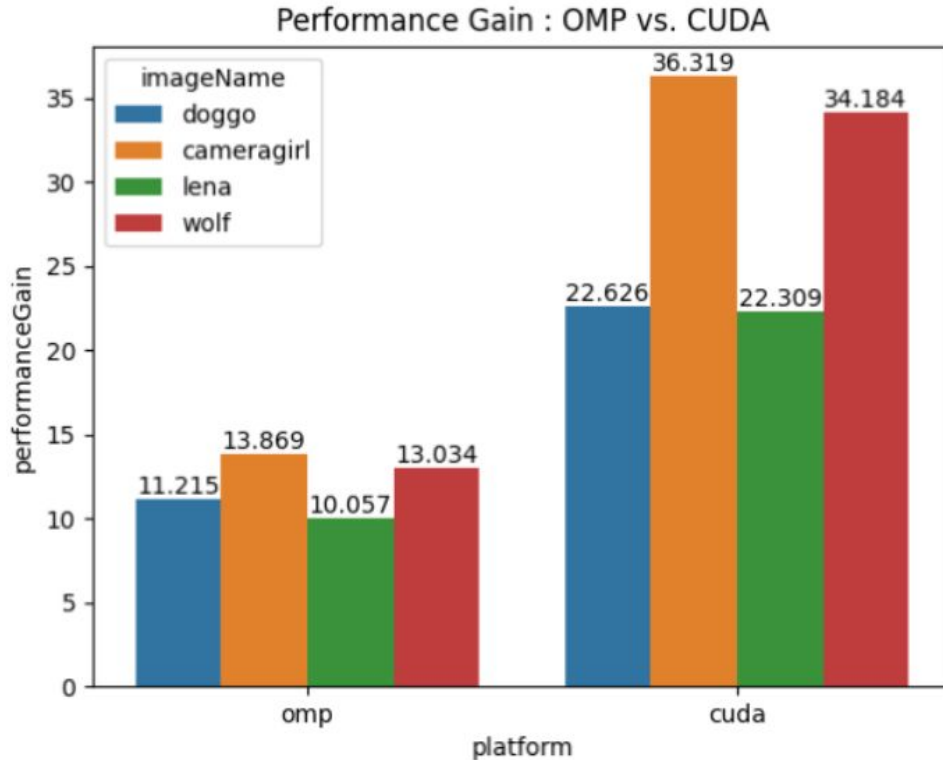


Dimensions : 3000 x 2003, Size : 334 KB



Threads used for OMP: 16  
Threads per block used for CUDA: 256

# Result - Grayscale (Performance Gain)

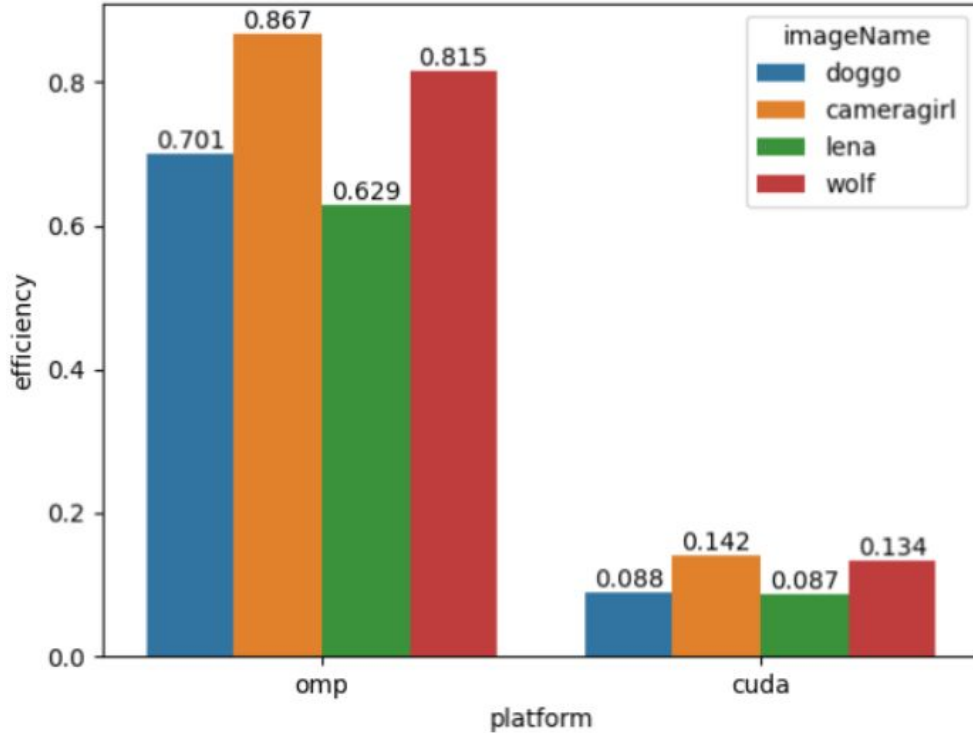


$$\text{Performance Gain} = \frac{T_{\text{serial}}}{T_{\text{parallel}}}$$

Threads used for OMP: 16  
Threads per block used for CUDA: 256

# Result - Grayscale (Efficiency)

Efficiency : OMP vs. CUDA



$$\text{Efficiency} = \frac{\text{Performance Gain}}{\text{Number of Processors}}$$

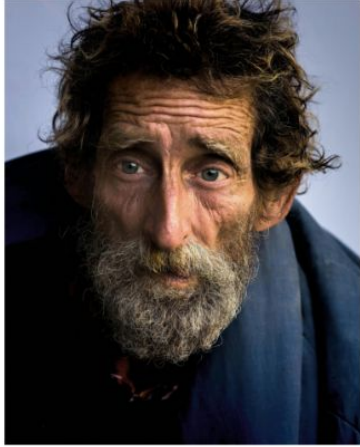
Threads used for OMP: 16  
Threads per block used for CUDA: 256

**With the success of parallelizing grayscale image enhancement, we proceeded with RGB image enhancement, by applying the same enhancement 3 times, 1 time on each BGR channels, and merging them in the end.**

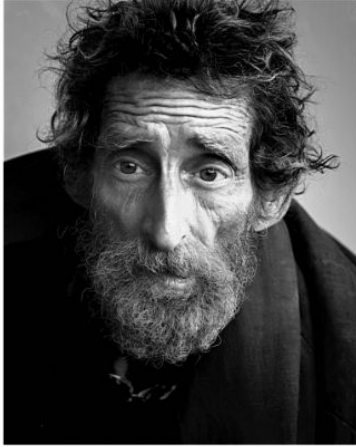


# Result - RGB

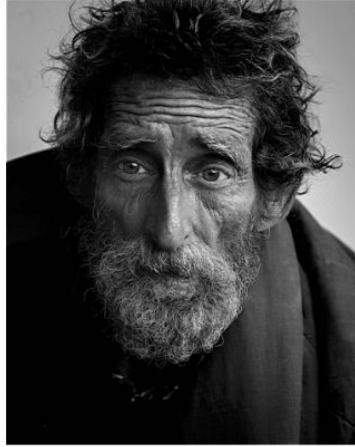
Original



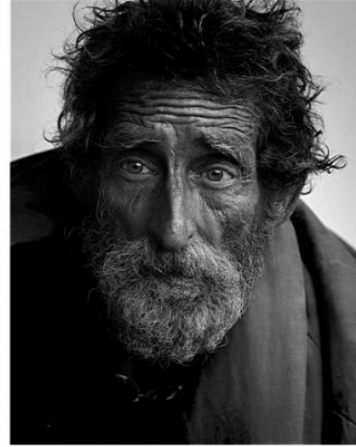
Red Processed



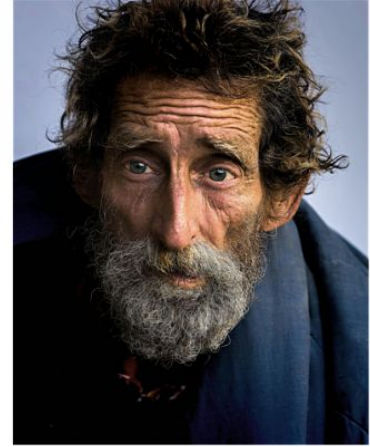
Green Processed



Blue Processed

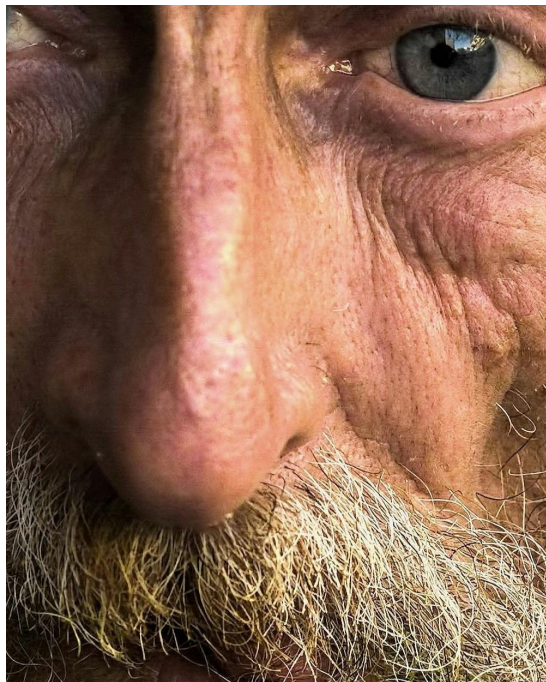


Final Result

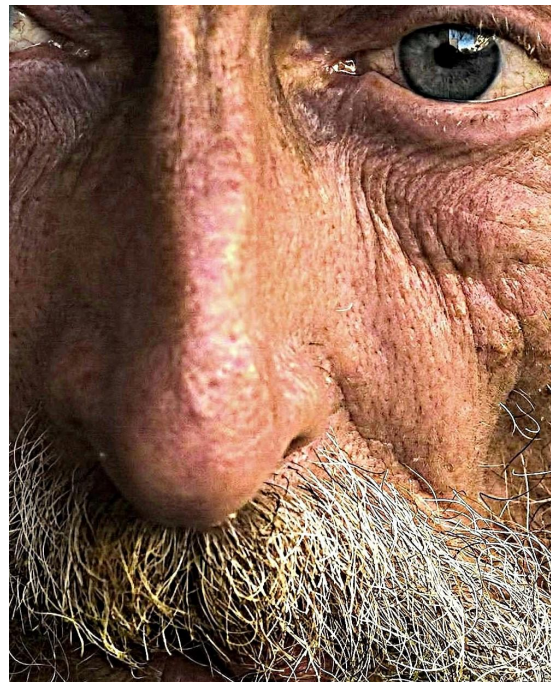


## Result - RGB ( Before & After )

Before

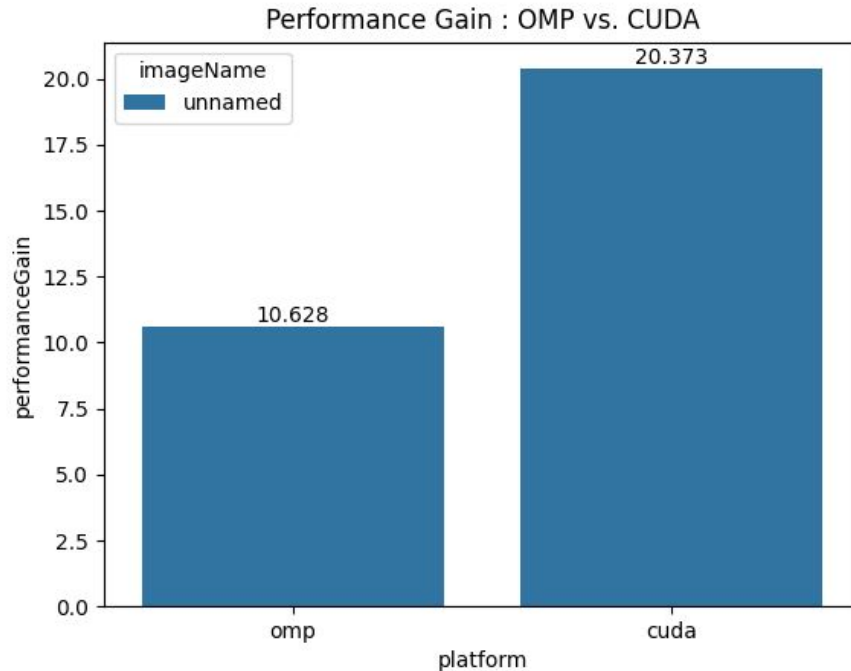


After



# Result - RGB (Performance Gain)

Dimensions : 4000 x 5000, Size : 2.74 MB

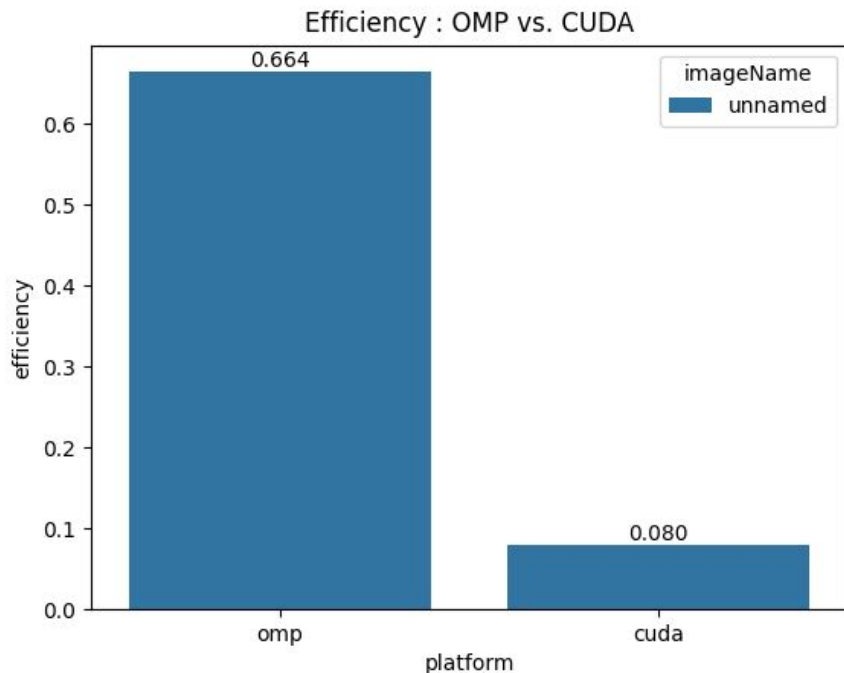


$$\text{Performance Gain} = \frac{T_{\text{serial}}}{T_{\text{parallel}}}$$

Threads used for OMP: 16  
Threads per block used for CUDA: 256

# Result - RGB (Efficiency)

Dimensions : 4000 x 5000, Size : 2.74 MB



$$\text{Efficiency} = \frac{\text{Performance Gain}}{\text{Number of Processors}}$$

Threads used for OMP: 16  
Threads per block used for CUDA: 256