School of Computer Science and Engineering

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AI6121 Computer Vision

Assignment 1

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Content

Introduction

Histogram Equalization (HE) is a popular image enhancement technique targeted at improving the contrast of an image by redistributing the pixel intensity values. The Global Histogram Equalization (GHE) algorithm works by adjusting the image's histogram to achieve a uniform distribution of intensity levels across the entire image. This process aims to enhance the visibility of details and improve the contrast in the images, particularly in images with poor contrast or small dynamic range.

Despite its effectiveness, the GHE algorithm is not without limitations. One significant drawback is its tendency to over-enhance images, leading to a loss of detail in both the bright and dark regions. This issue arises from the global nature of the algorithm, which applies the same transformation uniformly across the entire image, regardless of local variations in contrast in certain specific areas of the input image. Consequently, the GHE algorithm can sometimes produce unnatural or visually displeasing artifacts, especially in images with complex or uneven lighting conditions.

In this report, we explore potential enhancements to the traditional GHE algorithm to address its inherent flaws. Our goal is to investigate whether these enhancements can provide better image quality compared to the baseline GHE algorithm. We will evaluate various modified HE techniques and assess their performance through quantitative and qualitative analyses. By refining the histogram equalization process, we aim to achieve improved contrast enhancement while mitigating common issues such as detail loss and artifact introduction. The findings of this study a good application of histogram equalization in image processing to improve overall image quality for different image use cases.

Experiment Methodology

The Global Histogram Equalization (HE) algorithm will be implemented as a reference baseline for evaluating other HE algorithms. We will compute the average relative entropy, average Visual Information Fidelity (VIF), average absolute contrast, and average absolute brightness for all eight images. Additionally, each team member will perform a visual assessment of all 8 images processed by each HE algorithm. These results will be compared to the baseline data to determine the most effective HE algorithm.

Evaluation Methods

As mentioned previously, 5 evaluation metrics will be used to assess the improvements achieved by each HE enhancement method.

Visual Analysis by team members

One effective approach to assessing image enhancement is through visual comparison of the images before and after the different HE algorithms. If the images after the different types of HE algorithm show more details regardless of the bright and dark regions of the 8 images compared to the original image, it will be considered as an improvement.

However, while visual assessment is straightforward and can be quite telling, quantitative evaluation is also necessary for several reasons:

1. Subtle changes in the enhanced images may be difficult to detect visually, especially when we conduct tuning hyperparameter for the best HE model where minor adjustments such as a 0.1 change might go unnoticed.
2. Different teammates might have different aesthetic preferences to the images and think that enhanced images from other HE algorithms is more visually appealing
3. Inconsistency in the screen display and brightness of each team member's screen might affect the member's judgement of the enhanced images

Therefore, we will employ additional evaluation metrics commonly used in image enhancement to objectively measure the quality of our results.

Relative Entropy

The primary objective of Histogram Equalization is to achieve a uniform distribution of pixel intensity values within an image. Conceptually, a more uniform distribution of intensity values indicates a more effective enhancement of the input image. Information entropy serves as a valuable and straightforward metric for assessing the uniformity of this intensity distribution. A higher entropy value, derived from the intensity histogram, signifies a more even distribution of pixel values. The below figure shows that when the histogram is less even, it has a lower entropy value is 1.7315 than when the histogram is even, which has an entropy value of 2.585.

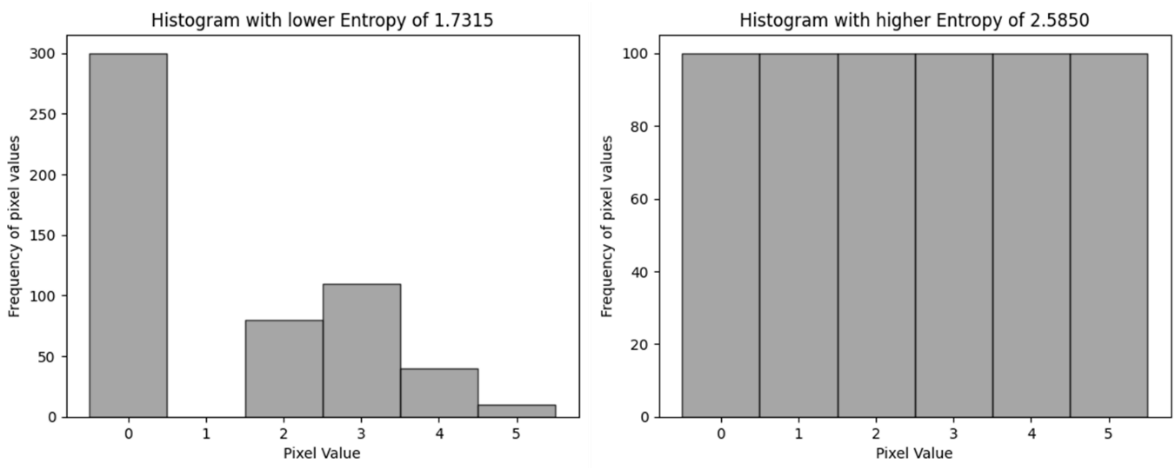


Fig 1: Histogram visualization of histograms with lower and higher entropy

In this report, we will use the relative entropy of the enhanced image to the original image as shown in the below formula to determine which type of HE algorithm gives a better enhancement to the images:

$$Relative\ entropy = \frac{entropy\ of\ enhanced\ image}{entropy\ of\ original\ image}$$

Based on the above equation, if the relative entropy exceeds 1, it indicates that the type of HE algorithm used has improved the image quality compared to the original. Conversely, if the relative entropy is less than 1, it signifies that the HE algorithm has produced images of lower quality than the original. The below shows the code snippet for calculating this:

```
def calculate_entropy(img):
  entrophies = []
  for i in range(3):
    Y = img[:,:,i]
    hist, _ = np.histogram(Y.flatten(), bins=256, range=(0, 256))
    pdf = hist / hist.sum()
    # Remove zero probabilities to avoid log(0)
    pdf = pdf[pdf > 0]

    # Calculate entropy
    entropy = -np.sum(pdf * np.log2(pdf))
    entrophies.append(entropy)

  return np.mean(entrophies)
```

To calculate entropy, the probability of each pixel value in each of the red, green and blue channel is found by dividing the count of each pixel value by the total number of image pixels. Probabilities less than 0 is filtered out. The entropy of the image is calculated as follows where x_i is each pixel:

$$entropy\ of\ image = -\sum_{i=1}^{n} p(x_i) log_2 p(x_i)$$

Consider all 3 colour channels as coloured can influence perceived brightness and contrast seen by the human eye. For example, different colours such as yellow, looks brighter to the human eye than blue, even if both colours might be of the same brightness. Colours with different hue saturation might make the image more contrasted such as by placing red and blue (both colours of the same brightness) beside each other as those 2 colours are far apart on the colour wheel as seen below:

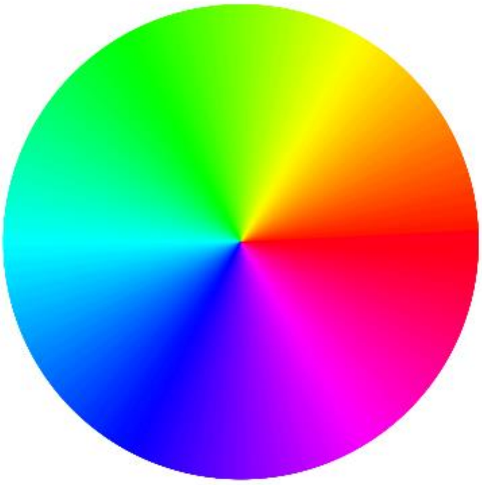


Fig 2: Colour wheel where red looks brighter than blue even though all colours are of same brightness

Visual Information Fidelity (VIF)

This is a method developed from Texas university to evaluates the preservation of visual information, providing insights into the quality of image processing methods in a way that aligns with human visual perception. It complements other metrics by focusing on how well the visual content of the image is retained after processing.

```
from sewar.full_ref import vifp
def calculate_vif(original, comparison):
   return vifp(original, comparison)
```

Looking at the code snippet above, by using the vifp method from sewar.full_ref package, parsing in the original image and enhanced image into the method can give the VIF value. If the VIF score is below 1, it indicated that the image after HE enhancement has less visual information compared to the original image. The image can be coloured or greyscale. A VIF score higher than 1, indicates that the image after HE enhancement has more visual information than the original image. If the VIF score is 1, it meant that the processed image has the same amount of visual information than the original image.

The vifp method evaluates the image in the luminance channel. The figure below illustrates that a VIF score greater than 1 corresponds to an image that is sharper and contains more detail. In contrast, a VIF score less than 1 reflects an image that appears blurrier and with reduced detail.

Reference VIF=1.0 | Contrast enhanced. VIF=1.10 | Blurred VIF=0.07

Fig 3: Visual comparison of different VIF score.

Nevertheless, there are some flaws to VIF. Although VIF is designed to align with human visual perception, it may not always capture perceptual aspects that are critical to subjective image quality, such as color fidelity and texture details. For example, after the enhancement, dark areas of the image might be over exposed to allows us to see the details in the dark areas but the VIF score for the image might be lowered due to the exposure.

Absolute Contrast

Absolute contrast measures the range of pixel intensity values within an image. In this report, we derive absolute contrast from the standard deviation of normalized luminance values in an image. Higher absolute contrast indicates better differentiation of intensity levels, which can enhance the visibility and overall quality of the image.

To calculate the contrast of an RGB image using standard deviation, the image is first converted into the YCbCr color space. The standard deviation of the Y channel is then computed, reflecting how much the luminance values deviate from the mean. A higher standard deviation indicates greater variability in brightness, corresponding to higher contrast in the image.

The Y channel is chosen to represent contrast because it directly corresponds to the luminance, the most critical factor in human perception of contrast. Human vision is more sensitive to brightness changes than to color changes, so focusing on the Y channel allows for a more accurate and meaningful measurement of contrast. This approach avoids the complexities and inaccuracies of color-based contrast calculations, making the Y channel the preferred choice.

```
# Contrast
def c_contrast(image):

  image_ycbcr = cv2.cvtColor(image, cv2.COLOR_RGB2YCrCb)
  Y = image_ycbcr[:, :, 0]
  Y_array = np.array(Y)
  norm =Y_array/255

  return np.std(norm)
```

A higher standard deviation indicates a greater spread of intensity values, implying higher contrast. Conversely, a lower standard deviation indicates a smaller range of intensity values, suggesting lower contrast.

Absolute Brightness

Absolute brightness is a measurement of the overall brightness level of an image which is calculated as the average pixel intensity as shown in the formula below:

$$Absolute\ Brightness = \frac{1}{N}\sum_{i=1}^{N} I_i$$

where N represents the total pixels in the image and I_i represents the intensity of the ith pixel.

This metric enables us to assess whether a specific HE algorithm has increased or decreased the image brightness. If the absolute brightness value is too high, it may result in information loss, causing many pixels to reach a '0' pixel value and making more areas of the image appear white, potentially obscuring image semantics. Conversely, a brightness value that is too low can cause more areas to appear black, which also represents a form of information loss.

```
def calculate_absolute_brightness(image):
    gray_image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
    brightness = np.mean(gray_image)
    return brightness
```

In the code snippet above, the color image is first converted to grayscale, before calculating the mean pixel value across all pixels in the image, which is that image's absolute brightness value.

Evaluation Methods Summary

Table 1: Summary of channel comparison amongst different metrics

	Visual Analysis	Relative Entropy	VIF	Absolute Contrast	Absolute Brightness
Channel	-	RGB	Luminance	Luminance	Luminance

Looking at the table above, all channels are considered in our evaluation metrics especially since the 8 sample images provided to the team are coloured. This is to ensure that information in each of the channels are captured so that the analysis by the team can be holistic. For Visual Analysis, the evaluation will be done by team members visually, so the term 'channel' does not apply since that is only applicable for algorithm-based analysis.

Baseline Results of Global HE algorithm

A greyscale image only contains 1 channel, the greyscale channel. Whereas a coloured image can contain 3 channels, namely red, green and blue channel.

Histogram Equalization (HE) is an image processing technique used to enhance the contrast of an image. For a coloured image, HE is applied to the luminance channel of the images which controls the brightness of the image. This prevents the colour of the images to be changed which might cause colour distortion of the output images.

The goal of HE is to adjust the intensity distribution of an image so that it covers the entire range of possible values more evenly. This is achieved by spreading out the most frequent intensity values over a wider range as shown in Fig 1, making low-contrast areas of the image more visible. Often, the complete even distribution of the gray-level pixel intensity cannot be achieved from the HE algorithm. Hence, Fig 4 shows an ideal scenario.

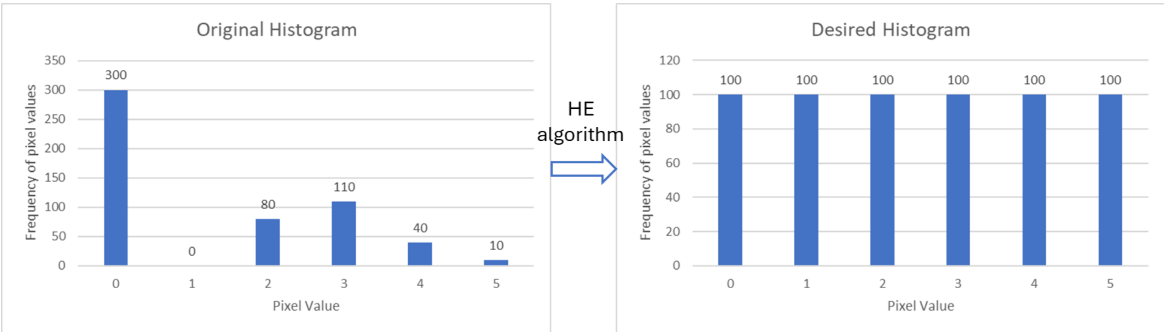


Fig 4: The purpose of HE algorithm is to try and flatten the grey-level histogram of an image.

Suppose the luminance channel of the input image f(x, y) is composed of the range 0 to L-1 where L-1 is the number of bins in the histogram, the below formula illustrates how each of the pixels in the input image will be enhanced:

$$s_k = C(r_k) = \sum_{i=0}^{k} P(r_i) = \sum_{i=0}^{k} \frac{n_i}{n}$$

where $0 \leq s_k \leq 1$ is the pixel value after the GHE algorithm, n_i represents the number of pixels having pixel value r_i, $P(r_i)$ represents the Probability Density Function (PDF) of r_i. Using the PDF, the Cumulative Density Function (CDF),(r_k), is defined.

HE Code Snippet

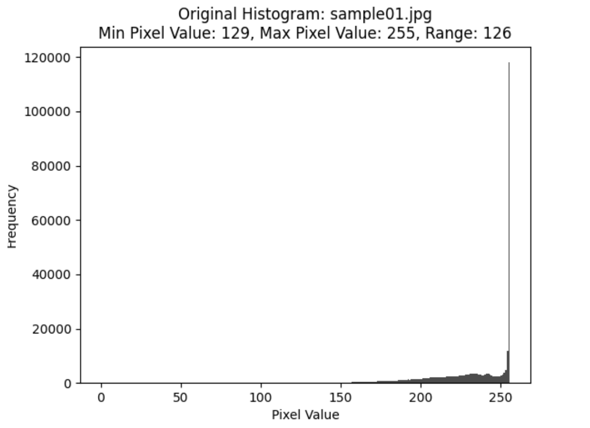
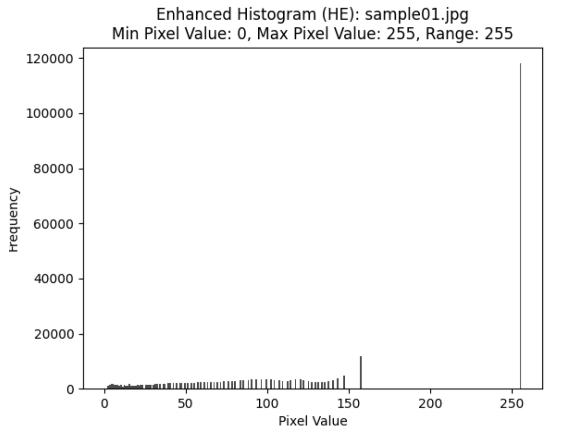
```
def calculate_histogram(image):
    histogram = np.zeros(256, dtype=int)
    for pixel in image.flatten():
        histogram[pixel] += 1
    return histogram

def calculate_cdf(histogram):
    cdf = histogram.cumsum()
    cdf_normalized = cdf * (255 / cdf[-1])
```

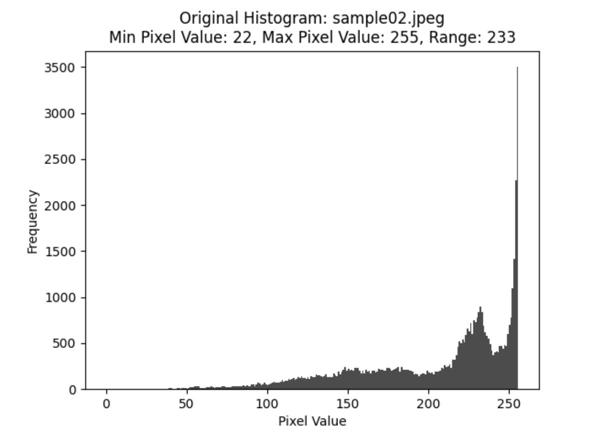
```
    return cdf_normalized.astype('uint8')

def apply_histogram_equalization(image, cdf):
    return cdf[image]

def histogram_equalization(image):
    histogram = calculate_histogram(image)
    cdf = calculate_cdf(histogram)
    return apply_histogram_equalization(image, cdf)

def enhance_color_image(image):
    # Convert the image from BGR to YUV
    img_yuv = cv2.cvtColor(image, cv2.COLOR_BGR2YUV)
    img_yuv[:, :, 0] = histogram_equalization(img_yuv[:, :, 0])
    enhanced_img = cv2.cvtColor(img_yuv, cv2.COLOR_YUV2BGR)
    return enhanced_img

listNames = ['sample01.jpg', 'sample02.jpeg', 'sample03.jpeg', 'sample04.jpeg', 'sample05.jpeg', 'sample06.jpg',
'sample07.jpg', 'sample08.jpg']

for name in listNames:
    # Load the original image
    original_img = cv2.imread('/content/drive/MyDrive/sampleimages/' + name)

    # Convert the image to grayscale for histogram plotting
    gray_original_img = cv2.cvtColor(original_img, cv2.COLOR_BGR2GRAY)

    # Apply manual HE to the image
    enhanced_img = enhance_color_image(original_img)
```

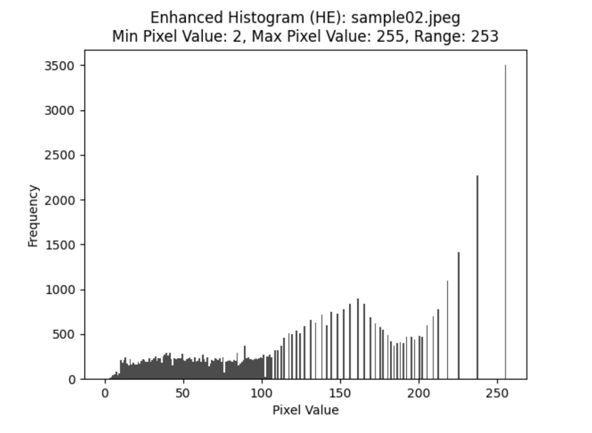
Looking at the code snippet above, all 8 sample images are iterated through the GHE algorithm. The images are converted to greyscale where the histogram of the frequency of pixel intensity ranging from 0 to 255 is calculated. The CDF of the histogram is then calculated and normalised to the range of 0 to 255 before applying the CDF to remap the pixel value of the original image.

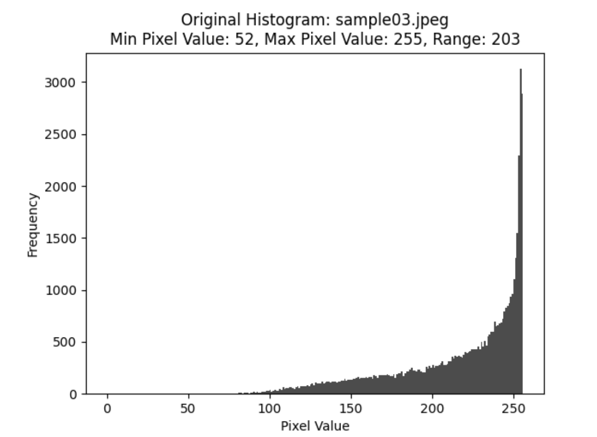
Experiment Results

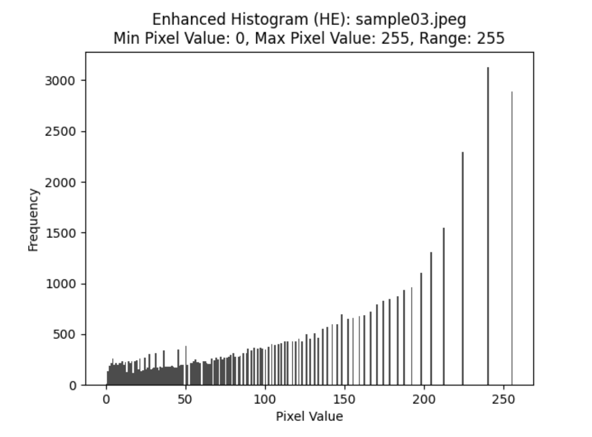
Table 2: Distribution of Histogram before and after the GHE image enhancement

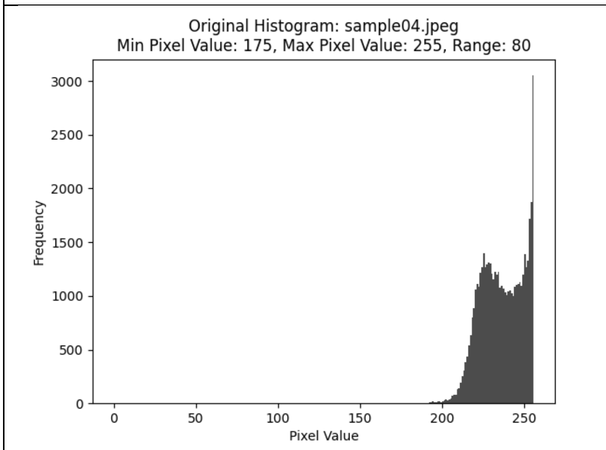
Original Histogram	**GHE Histogram**
	

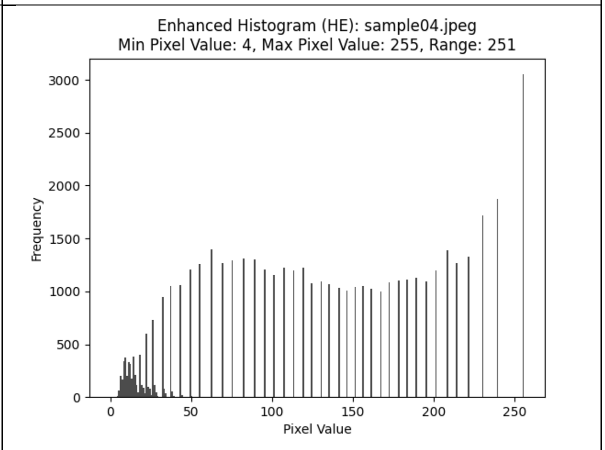

Original Histogram: sample02.jpeg
Min Pixel Value: 22, Max Pixel Value: 255, Range: 233
Frequency
Pixel Value

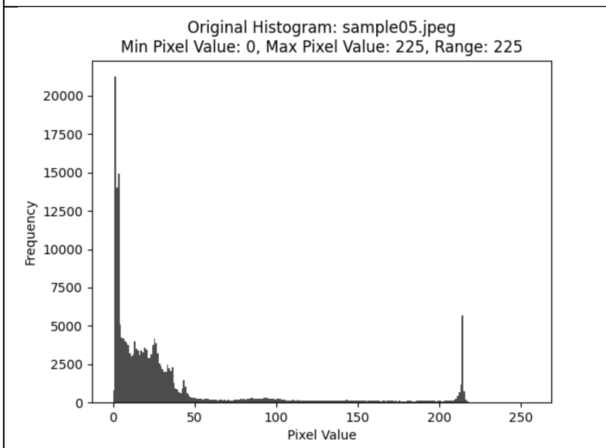

Enhanced Histogram (HE): sample02.jpeg
Min Pixel Value: 2, Max Pixel Value: 255, Range: 253
Frequency
Pixel Value

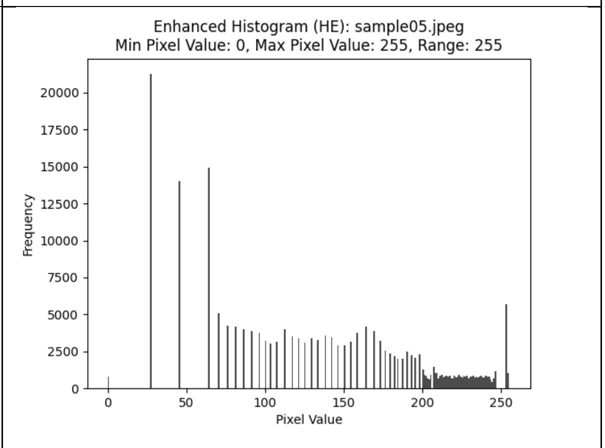

Original Histogram: sample03.jpeg
Min Pixel Value: 52, Max Pixel Value: 255, Range: 203
Frequency
Pixel Value

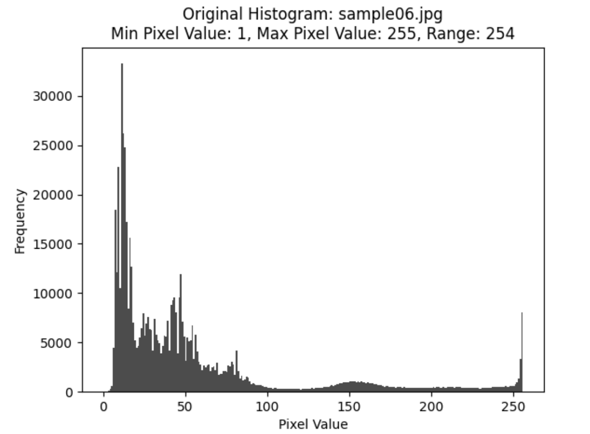

Enhanced Histogram (HE): sample03.jpeg
Min Pixel Value: 0, Max Pixel Value: 255, Range: 255
Frequency
Pixel Value

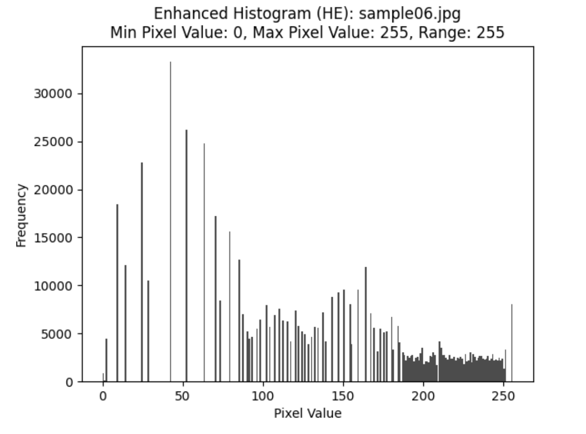

Original Histogram: sample04.jpeg
Min Pixel Value: 175, Max Pixel Value: 255, Range: 80
Frequency
Pixel Value

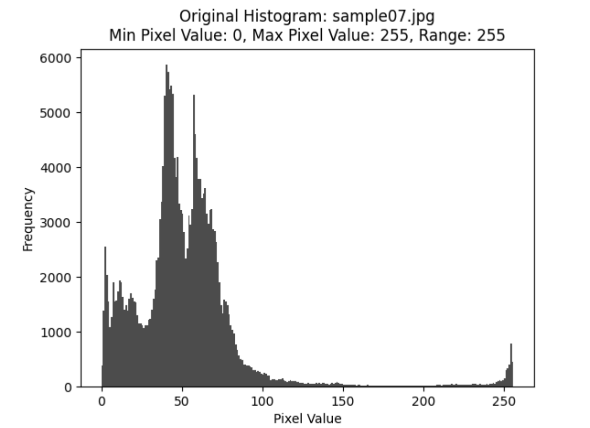

Enhanced Histogram (HE): sample04.jpeg
Min Pixel Value: 4, Max Pixel Value: 255, Range: 251
Frequency
Pixel Value

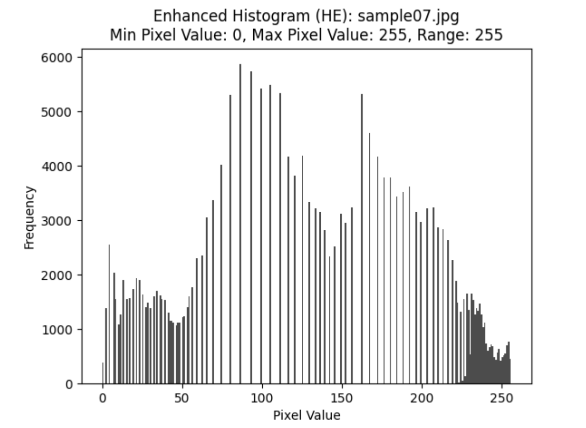

Original Histogram: sample05.jpeg
Min Pixel Value: 0, Max Pixel Value: 225, Range: 225
Frequency
Pixel Value

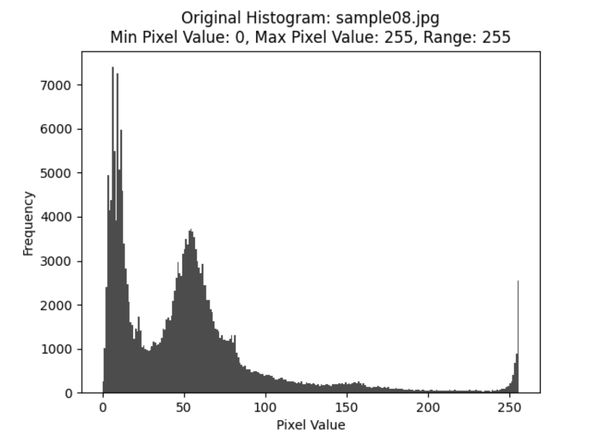

Enhanced Histogram (HE): sample05.jpeg
Min Pixel Value: 0, Max Pixel Value: 255, Range: 255
Frequency
Pixel Value


Original Histogram: sample06.jpg
Min Pixel Value: 1, Max Pixel Value: 255, Range: 254
Frequency
Pixel Value


Enhanced Histogram (HE): sample06.jpg
Min Pixel Value: 0, Max Pixel Value: 255, Range: 255
Frequency
Pixel Value


Original Histogram: sample07.jpg
Min Pixel Value: 0, Max Pixel Value: 255, Range: 255
Frequency
Pixel Value


Enhanced Histogram (HE): sample07.jpg
Min Pixel Value: 0, Max Pixel Value: 255, Range: 255
Frequency
Pixel Value


Original Histogram: sample08.jpg
Min Pixel Value: 0, Max Pixel Value: 255, Range: 255
Frequency
Pixel Value

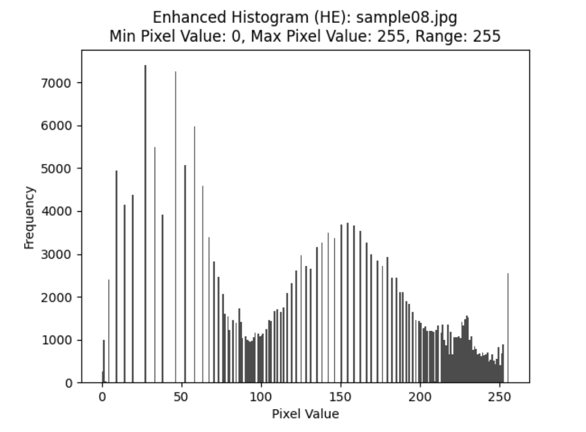

Enhanced Histogram (HE): sample08.jpg
Min Pixel Value: 0, Max Pixel Value: 255, Range: 255
Frequency
Pixel Value

Table 3: Comparison of original images and images after the GHE image enhancement

Original Image	GHE Processed Image
	
	
	
	

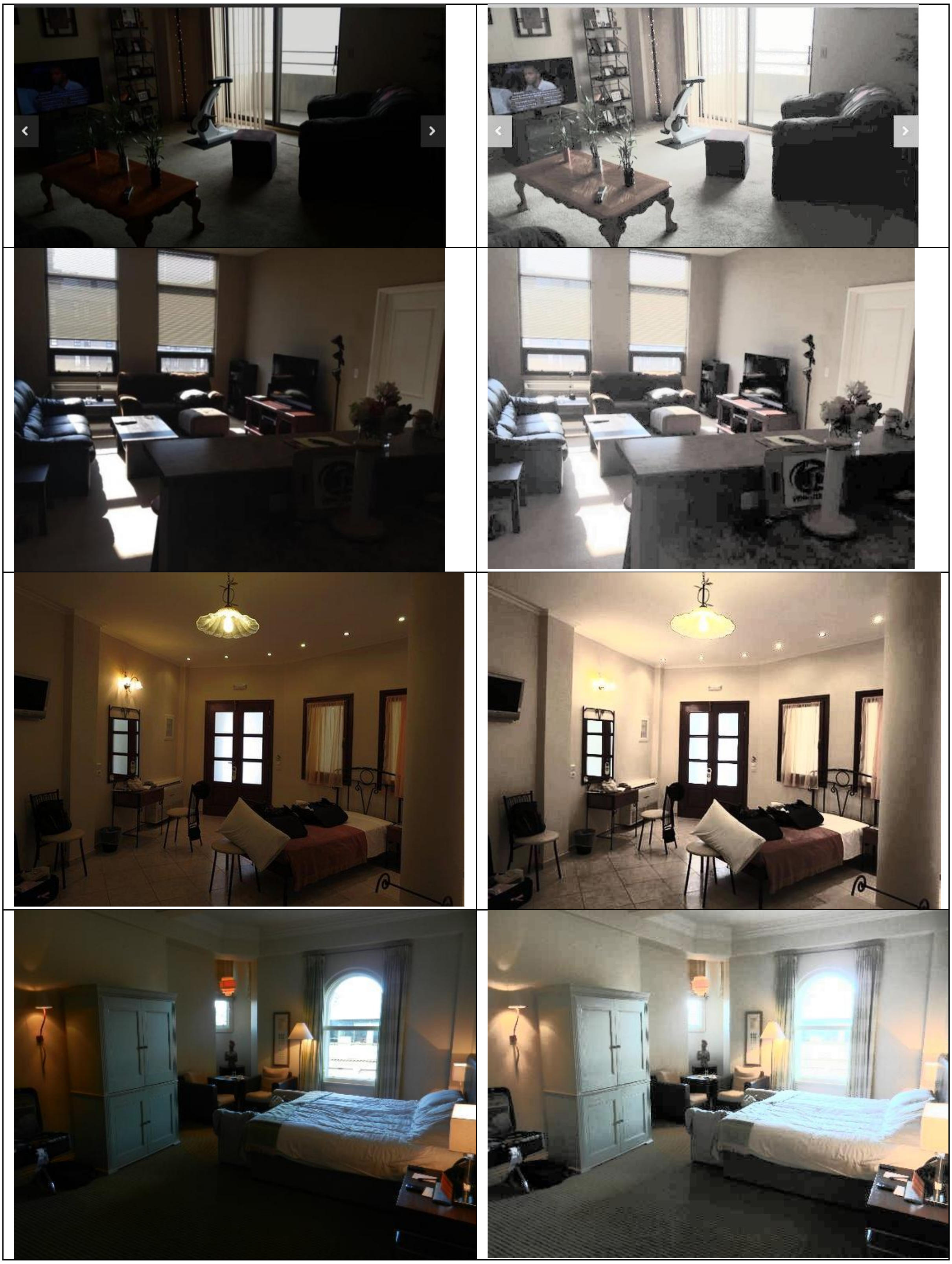


Table 4: Success metrics comparison for original images and GHE enhanced images across all 8 images

Image Type	Average Absolute Contrast	Average Absolute Brightness	Average Relative Entropy	Average VIF
Original	0.165279	136.319149	1	1
GHE Enhanced	0.296226	131.79478	1.138139	0.753653

Pros & Cons of GHE

Pros

The enhanced images in Table 3 demonstrate that the Global Histogram Equalization (GHE) effectively improves the contrast of the original images, significantly enhancing the visibility of finer details. This improvement is further validated by the histograms of the enhanced images in Table 2, which show a more even and widespread pixel distribution across all eight images compared to the original images. Below are examples of how GHE improved visibility in each image:

Sample Image 01: The overall visibility of the buildings in the image increased and brickwork can be seen on certain buildings

Sample Image 02: The overall visibility of the cat appearance is enhanced because of the contrast enhancement between the patches of dark and light cat fur.

Sample Image 03: The details of the buildings, roads, and hilly terrain are more clearly defined

Sample Image 04: The trees and pathway are more clearly defined, with darker shadows and more visible textures in the foliage.

Sample Image 05: Objects like the remote control, flower pots, and the TV screen content in the room are more identifiable due to the enhanced contrast.

Sample image 06: Items such as the logo at the bottom right corner and the shelf near the windows are more distinct with improved visibility.

Sample image 07: The luggage and its items in the bottom left corner of the image are easier to identify with enhanced contrast

Sample image 08: The luggage and its items beside the wardrobe and the statue in the far corner of the room became more visible.

Moreover, GHE is advantageous due to its simple implementation and computational efficiency, as it employs a global approach. However, despite the improvements, certain areas in some images remain poorly enhanced and unsatisfactory after applying GHE. We will address these issues in more detail in the following "Cons" section.

Cons

As mentioned in the “Pros” section, although the histogram is more evenly distributed after applying GHE, certain sections of the histograms still remain densely populated. For instance, bright images such as enhanced images 1, 2, 3, and 4 still have a significant concentration of pixels in the lower value range of 0 to 100. Darker images like 5, 6, 7, and 8 continue to show a high pixel density in the upper value range of 200 to 255 after GHE algorithm. This indicates that the Global Histogram Equalization (GHE) algorithm is limited in its ability to adjust the overall brightness of the images. Despite the GHE image enhancement process, bright images remain relatively bright, and dark images retain their darker tones. This is because the GHE algorithm works by redistributing the pixel intensities based on the CDF of the entire image and might not adjust the brightness effectively in certain areas of the image.

Looking at Table 2, we can see that the range of pixel values of histogram of the enhanced images are not 255 for all images, such as for sample image 2 and 4. This could be because original images of both images have very low dynamic range where majority of the image pixels are high. The GHE algorithm is unable to stretch the high pixel values from the original images across the entire pixel value range of 255.

Upon reviewing the processed images, it is evident that enhanced images 1, 2, 3, and 4 exhibit increased contrast but also display a more pixelated and noisier appearance with outlier pixels following the GHE enhancement. This suggests that the contrast levels for these enhanced images are excessively high when the pixel values are redistributed, leading to information loss and making the images less visually appealing. In the case of enhanced images 5 and 6, the brightness is elevated to the point where the colours appear faded, and the contrast is so intense that the images become pixelated.

For enhanced images 7 and 8, the bright areas, such as the light bulb in image 7 and the scene outside the window in image 8, are over-brightened and over-contrasted, causing the semantics of the light bulb and the objects outside the window to diminish significantly. This results in a loss of information, as the bright objects are no longer clearly visible in the images.

As observed in Table 4, there is a general decrease in brightness and an increase in contrast in the GHE-enhanced images. The relative entropy and VIF for the original images are both 1, as they are compared against themselves. Following GHE enhancement, the relative entropy increases, which aligns with expectations since Table 2 indicates that the histograms of the eight images become more evenly distributed post-GHE enhancement. However, the VIF drops below 1 after GHE enhancement, likely due to the flaws in the enhanced images, as discussed in the preceding paragraphs.

Since the GHE has room for improvement, we will explore other HE algorithms which are modifications of the GHE algorithm which aims to enhance the GHE algorithm. We will evaluate the results of the performance of those other HE algorithms on the 8 images to determine if they outperform or underperform compared to the GHE baseline algorithm.

Enhancements

Contrast Limited Adaptive Histogram Equalization (CLAHE)

Contrast limited adaptive histogram equalization (CLAHE) is a variation of adaptive histogram equalization (AHE) and it is meant to take care of over-amplification of the contrast. Unlike Histogram Equalization (HE), which enhances the entire image globally, this technique divides the original input image into non-overlapping blocks, called tiles, and enhances the tiles individually. With this localized equalization technique, CLAHE often provides better image contrast than HE. In CLAHE, two hyperparameters - Clip Limit and Tile Grid Size are used to control the quality of the image.

The Tile Grid Size hyperparameter sets the number of tiles in the row and column, allowing the program to know the dimensions of the tiles that need to be enhanced. Smaller tile sizes allow CLAHE to apply local contrast adjustments more granularly. This can improve detail and contrast in smaller regions of the image. If the tile size is too small, it might enhance noise or artifacts, as the algorithm focuses on very small areas that may contain noise. Larger tile sizes result in fewer tiles, which means each tile covers a larger portion of the image. This can make the contrast adjustment smoother and less prone to noise. Nevertheless, larger tiles may not handle local variations as effectively, potentially resulting in less detail and contrast enhancement in specific regions of the image.

The Clip Limit hyperparameter is the option to overcome the noise problem by preventing the algorithm from over-amplification of noise in relatively homogenous regions of an image [1]. It is a floating-point number typically ranging from 1.0 to 10.0 or higher. Before the computation of Cumulative Distribution Function (CDF), the histogram's intensity values are clipped if they exceed the clip limit. If a histogram bin exceeds the clip limit, the excess pixels are redistributed evenly to other bins ensuring that the pixels are more evenly spread across the intensity range and that no single intensity range dominates the processed image. A low clip limit reduces the extent of the contrast enhancement of CLAHE. This might lead to a more uniform image and less noise though fine details will be less visible. On the other hand, a high clip limit will increase the contrast enhancement of CLAHE, leading to the fine details and texture being more prominent but it increases the risk of artefacts being introduced and noise in low contrast areas. If the clip limit is not chosen correctly, the enhanced image may have significantly worse contrast and overall quality than the original image in some cases.

Once all tiles have been processed, they need to be combined smoothly to prevent noticeable seams between them. Bilinear interpolation is employed to blend the edges of adjacent tiles, creating a more natural transition and eliminating any harsh boundaries or artifacts[5]. The algorithm for CLAHE is shown below:

1. Input the image and calculate the grid size based on image dimension

2. The image is divided into smaller, non-overlapping regions called tiles specified by Tile Grid Size.
3. For each tile, Histogram Equalization process is applied:
    a. Calculate the histogram of pixel intensities
    b. Apply contrast limiting by clipping the histogram specified by the Clip Limit
    c. Find the CDF of the clipped histogram
    d. Apply equalization using the normalized CDF
4. Apply bilinear interpolation to smooth the transitions between adjacent tiles.

Hyperparameter Tuning

Both hyperparameters of clip limit and tile grid size are going to be tuned using the grid search method. Different combinations of tile grid size will be tested with different clip limits.

Table 5: Tuning Results of clip limit and tile grid size of CLAHE

Clip Limit	Tile Grid Size	Average Absolute Contrast	Average Absolute Brightness	Average Relative Entropy	Average VIF
2	8 x 8	0.201752	136.816754	1.115410	**0.956551287**
2	16 x 16	0.174379	**145.098188**	1.037365	0.851014995
2	20 x 20	0.184681	140.7212976	1.069310	0.846636312
2	32 x 32	0.197994	137.1499648	1.087019	0.750880279
4	8 x 8	0.226955	135.5262421	1.162529	0.877226459
4	16 x 16	0.209304	138.7856039	1.131279	0.797770767
4	20 x 20	0.206581	138.4115198	1.127116	0.760527453
4	32 x 32	0.200192	140.4507569	1.118113	0.698509271
6	8 x 8	0.243022	134.4094731	1.185465	0.833633845
6	16 x 16	0.227240	135.5650863	1.164289	0.747505299
6	20 x 20	0.220818	136.7901228	1.155405	0.71413072
6	32 x 32	0.206870	141.8725126	1.132505	0.669403746
8	8 x 8	**0.252020**	134.3102175	**1.197952**	0.806261507
8	16 x 16	0.235324	135.8769804	1.178310	0.722337874
8	20 x 20	0.230716	136.0554314	1.172716	0.681934427
8	32 x 32	0.209440	143.9923938	1.140514	0.644802221

Looking at the results above, clip limit 2 of tile size 16 x 16 produces the brightest images across all 8 images and clip limit 6 of time size 8 x 8 produces the most contrasted images across all 8 images. Nevertheless, highest average contrast and highest average brightness does not mean the images are the best looking as the images might be overly-too contrasted or over-too bright, leading to information loss.

As the clip limit increases, we did see more contrasted images produced but those images look highly pixelated and overexposed. A lot of artifacts were also produced around the edges of the objects in the images as shown below. This shows that even though the absolute contrast and average relative entropy might be high, it does not necessarily mean that the processed images will be visually appealing to the human eye. Hence, visual analysis plays an important role in evaluating processed images from CLAHE.

Fig 3: Processed images from clip value = 8 and grid size = 32 x 32 from CLAHE

After visual analysis of the processed images, the team concluded that smaller clip values give more visually appealing images. The team came up with a new range for the grid search so that values closer to the hyperparameters giving more visually appealing processed images are explored. The results are shown below:

Table 6: Results from grid search tuning of clip limit and tile grid size.

Clip Limit	Tile Grid Size	Average Absolute Contrast	Average Absolute Brightness	Average Relative Entropy	Average VIF
2	8 x 8	0.201752	**136.816754**	1.115410	**0.956551**
2	16 x 16	0.174379	145.098188	1.038500	0.851015
2	32 x 32	0.197994	137.149965	1.082411	0.750880
3	8 x 8	**0.215812**	136.111449	**1.143537**	0.911954
3	16 x 16	0.195271	140.932738	1.089794	0.838457
3	32 x 32	0.197011	139.127784	1.098927	0.718140

From the results of the above table, we see that clip limit 2 with tile grid size of 8 x 8 and clip limit 3 with tile grid size 8 x 8 gives better metric results than other clip limit and tile grid size combinations when comparing across all 8 images. Images from clip limit 2 gives higher absolute contrast and lower absolute contrast than clip limit 3 for the same tile grid size of 8 x 8. Clip limit of 2 gives higher average VIF and lower relative entropy than that of clip limit 3.

As both clip limit 2 and clip limit 3 with a tile grid size of 8 x 8 shows very similar results, we will move on to evaluate the visual appearance of each image from clip limit 2 and clip limit 3, both with the same tile grid size of 8 x 8 for the team member to decide which clip limit to go for.

Results and Discussion

Table 7: All 8 enhanced images with tile grid size of 8 x 8 and clip limit of 2 and 3 for visual comparison.

Clip Limit = 2, Tile Grid Size = 8 x 8	**Clip Limit = 3, Tile Grid Size = 8 x 8**	**Member's comments**
		Colour and contrast of image from Clip Limit = 3 is clearer.
		When looking at the cat's eyes, the contrast from Clip Limit = 2 is better.
		The overal contrast in image from Clip Limit = 2 is better such as the details of the mountains and the mountains' shadows are seen clearer.
		Image from Clip Limit = 2 gives better contrast and colouring to the plants.
		Image from Clip Limit = 3 gives better contrast such as the person in the television screen can be seen clearer.

		Image from Clip Limit = 3 is better as the painting at the bottom right of the image can be seen clearer.
		Image from Clip Limit = 3 has better contrast and show more details of the bags on the bed.
		Image from Clip Limit = 3 is better as the shadows of the bed can be seen clearer.

From the members' comments in the above table, clip limit 3 with grid tile size 8 x 8 produces 5 images nicer than that from clip limit 2. Hence, we conclude that clip limit 3 and grid tile size 8 x 8 are the optimal hyperparameter in the CLAHE algorithm when comparing results over all 8 images. The below table shows the comparison of original images, images after GHE enhancement and images after CLAHE enhancement.

Table 8: comparison of original images and processed images after GHE baseline and CLAHE algorithm

Original	**GHE (Baseline)**	**CLAHE (clip = 3, grid = 8x8)**
 Contrast: 0.10, Entropy: 4.78, Brightness: 234.94	 Contrast: 0.36, Entropy %: 1.13, Brightness: 147.31, VIF: 0.68	 Contrast: 0.21, Entropy %: 1.17, Brightness: 209.17, VIF: 1.01

Contrast: 0.19, Entropy: 6.64,
Brightness: 189.64

Contrast: 0.29, Entropy %: 1.05,
Brightness: 118.30, VIF: 0.60

Contrast: 0.22, Entropy %: 1.09,
Brightness: 172.63, VIF: 0.68

Contrast: 0.16, Entropy: 6.60,
Brightness: 215.78

Contrast: 0.30, Entropy %: 1.14,
Brightness: 129.03, VIF: 0.46

Contrast: 0.26, Entropy %: 1.14,
Brightness: 179.50, VIF: 0.72

Contrast: 0.05, Entropy: 5.64,
Brightness: 233.30

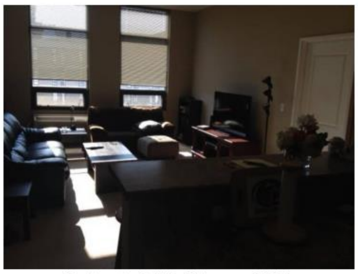
Contrast: 0.29, Entropy %: 1.32,
Brightness: 128.25, VIF: 0.93

Contrast: 0.13, Entropy %: 1.22,
Brightness: 204.13, VIF: 0.98

Contrast: 0.22, Entropy: 5.97,
Brightness: 35.75

Contrast: 0.28, Entropy %: 1.15,
Brightness: 130.34, VIF: 0.83

Contrast: 0.24, Entropy %: 1.20,
Brightness: 63.36, VIF: 1.03



Contrast: 0.24, Entropy: 6.72,
Brightness: 53.88

Contrast: 0.28, Entropy %: 1.08,
Brightness: 128.11, VIF: 0.84

Contrast: 0.24, Entropy %: 1.10,
Brightness: 74.83, VIF: 1.01

For sample image 01, a first glance reveals that the HE processed image is much darker than the CLAHE processed image, with darker patches dominating most of the foreground, midground, and background. In the foreground, the HE processed image makes it difficult to distinguish the texture of the tree on the left side, while in the CLAHE processed image, the entire tree is clearly visible. In the midground, the buildings with Chinese characters at the top are almost 90% covered by dark patches in the HE processed image. In the background, particularly in the top right corner, the HE processed image obscures further and smaller details with large patches of black shadows, whereas the CLAHE processed image allows for clear identification of areas containing trees or buildings. The CLAHE processed image is significantly brighter(209.17 brightness level), enhancing the visibility of finer details, including the trees and background buildings. The high contrast of the HE processed image results in a significant loss of visual details, reflected in a VIF of 0.68. In contrast, the CLAHE processed image maintains better entropy (1.17%) and provides a substantial improvement by preserving more visual information, achieving a VIF of 1.01. Overall, for this image, CLAHE performed better in overall visual clarity and detail preservation without compromising brightness.

For sample image 02, HE processed image has a higher contrast (0.29) compared to the CLAHE processed image (0.22), resulting in more pronounced differences between light and dark areas. However, this also leads to some regions being dominated by darker shadows, making the overall image appear darker. Despite the HE processed image's higher contrast, the patterns in the right-hand corner of the image are clearer and more discernible in the CLAHE processed image. Additionally, CLAHE processed image has a slightly higher entropy percentage (1.09% vs. 1.05%), indicating more detail or variation in pixel intensity. It also exhibits better VIF at 0.68, suggesting a higher preservation of visual details compared to the HE processed image's VIF of 0.60. Overall, CLAHE processed image is brighter, maintains more visual information, and provides clearer patterns without compromising the overall visual appearance of the image.

For sample image 03, HE processed image has a contrast of 0.30, offering slightly sharper edges but at the expense of darker areas, particularly in the shadows around the buildings and ground. CLAHE processed image has a lower contrast of 0.26, providing a more balanced light distribution, resulting in a softer but more evenly lit scene. Both images have the same entropy percentage (1.14%), indicating similar levels of detail. However, CLAHE processed image is significantly brighter (179.50 brightness level) than HE processed image (129.03 brightness level), which enhances the visibility of both shadowed and well-lit areas, making details clearer. Additionally, the CLAHE processed image exhibits a much higher VIF of 0.72, compared to 0.46 for the HE processed image, indicating that it preserves more visual information and detail, making it the clear winner.

For sample image 04, the HE processed image has a higher contrast (0.29), making edges more distinct but also introduces darker shadows, particularly around the trees and pathway. This higher contrast also darkens the artifact line that was originally present in the left-hand corner of the original image cutting across the tree leaves, making it more prominent and covering some of the finer details of the leaves. As a result, parts of the foliage lose their clarity. In contrast, the CLAHE processed image, with its lower contrast, avoids this issue, presenting a softer and more uniform light distribution. This results in a brighter, more evenly lit scene where details like the tree leaves remain more visible. The HE processed image has a slightly higher entropy percentage of 1.32%, indicating that it contains more detail or variation in pixel intensity. However, the presence of the artifact and the darker shadows may compromise the visibility of these details. The CLAHE processed image, with slightly lower entropy at 1.22%, still retains a comparable level of detail but without the interference of such artifacts, ensuring a more natural and clear representation. Finally, the CLAHE processed image is significantly brighter, enhancing the visibility of the overall scene. This increase in brightness makes the entire image appear lighter, allowing for better visibility of the pathway and the surrounding trees.

For sample images 05 to 08, a consistent pattern emerges when comparing HE processed images to CLAHE processed images. In the HE processed images, any prominent light source tends to cause overexposure in the surrounding areas, leading to a significant loss of detail, particularly in darker regions where the heightened brightness washes out subtle variations. While the lower brightness in CLAHE processed images might initially make them appear darker, it actually enhances the visibility of intricate details, especially in shadowed areas.

This difference is evident in each sample image:

Sample Image 05: The sunlight streaming through the glass doors is excessively bright, making it difficult to distinguish the individual grills in the door structure.

Sample Image 06: The sunlight passing through the windows and window grills is overly intense, washing out the window grills and obscuring the details of the buildings outside.

Sample Image 07: The multiple light sources from the hanging ceiling lights and the wall light are too bright, concealing the design details of the lights.

Sample Image 08: The sunlight coming through the windows is overly bright, making the buildings outside the windows indistinguishable.

In terms of VIF, the CLAHE processed images consistently preserve more information and visual detail due to their more balanced contrast and brightness levels.

Based on the comparisons of the images above, we can draw several conclusions about the effectiveness of Global Histogram Equalization (HE) versus Contrast Limited Adaptive Histogram Equalization (CLAHE).

Global Histogram Equalization (HE) tends to enhance contrast by uniformly distributing pixel intensity values across the entire image, resulting in sharper edges and more pronounced differences between light and dark areas. However, this global adjustment often leads to overexposure in areas with strong light sources, causing a significant loss of detail, particularly in the shadowed regions. The HE processed images frequently exhibit overly bright highlights and obscured details in both bright and dark areas, reducing overall visual information fidelity.

On the other hand, CLAHE offers a more nuanced approach by applying localized contrast adjustments within smaller regions of the image. This method avoids the pitfalls of overexposure and overly dark shadows, as seen in HE processed images. CLAHE enhances local details, particularly in areas with subtle variations in intensity, and preserves a more natural and balanced appearance throughout the image. While the CLAHE processed images may initially appear less dramatic due to lower contrast, they excel in maintaining detail, especially in shadowed areas, and avoid the harsh extremes seen in HE processed images.

Overall, CLAHE proves to be better than HE for enhancing these 8 images where preserving local details and avoiding overexposure are critical.

Dynamic Histogram Equalization (DHE)

DHE as illustrated by Wadud et al in the paper *'A Dynamic Histogram Equalization for Image Contrast Enhancement'* is an image processing technique designed to enhance contrast more effectively than traditional histogram equalization [2]. Unlike standard methods, which apply a uniform adjustment across the entire image, DHE divides the image into segments and adjusts the contrast locally. This approach preserves important details and avoids common issues like over-enhancement or noise amplification, resulting in a more natural-looking image with improved visibility in both bright and dark regions. DHE is particularly useful in applications like medical imaging, satellite imagery, and photography.

Algorithm steps for DHE

1. Identify Local Minima

Smooth the histogram to reduce noise and identify significant local minima between every significant peak, also the first and last non-zero are considered as local minima. In the figure below, the histogram has its first and last minima at the pixel value of 0 and 255, respectively.

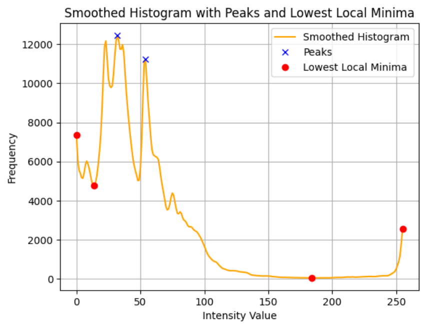


Fig 4: Histogram with first and last minima at pixel value of 0 and 255

2. Histogram Splitting

The histogram is divided into sub-histograms based on these local minima. Each segment is bounded by a local minimum on either side. See the sub-histogram boundary as the following.

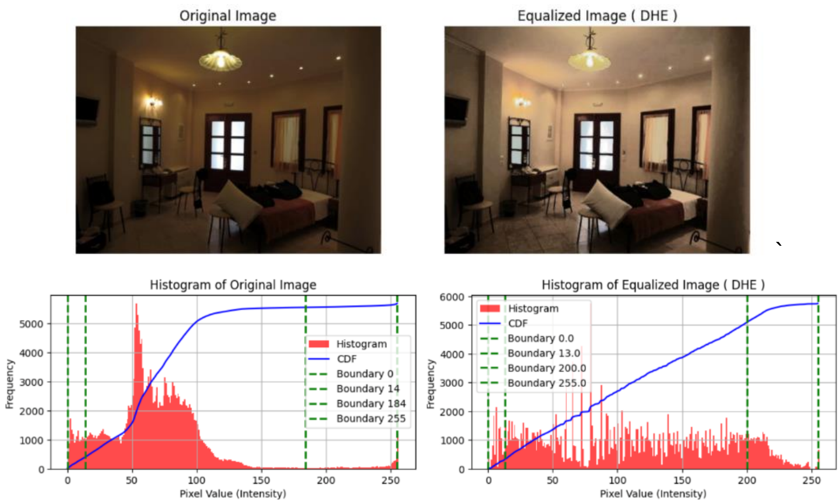


Fig 5: Original and enhanced images with their respective Histograms

3. Grey level Allocation

The sub-histogram span range is defined by the formula below:

$$span_i = m_i - m_{i-1}$$

$$range_i = \frac{span_i}{\Sigma\ span_i}(L-1)$$

$span_i$ = dynamic GL (GreyLevel) range used by sub-histogram i in input image.
m_i= i-th local minima in the input image histogram.
$range_i$= dynamic gray level range for sub-histogram i in output image.

However, if the input image already spans the full range of grey levels (GL), the sub-histogram cumulative frequency (CF) is used to determine the grey levels instead of the span level, as following

$$factor_i = span_i\ (\log CF_i\ )^x$$

$$range_i = \frac{factor_i}{\Sigma\ factor_i}(L-1)$$

where,
CF_i = the summation of all histogram values of ith sub- histogram.
x = amount of emphasis given on frequency.

Therefore, the dominant sub-histogram with higher pixel intensity is allocated a wider range.

4. Apply histogram equalization to each sub-histogram

With the new given range, each sub-histogram is then equalized separately. Therefore, the contrast adjustment is done locally within sub-histogram, rather than across the entire image.

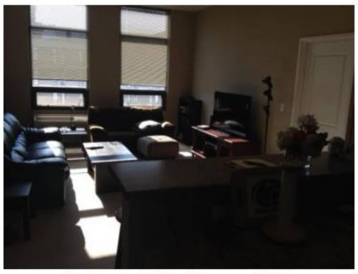
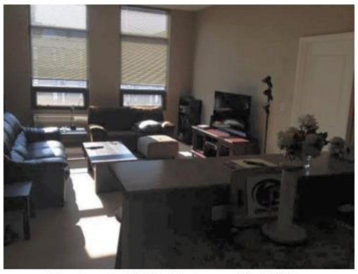
5. Recombine the sub-histograms

After equalizing each sub-histogram, the segments are recombined to form the final image.

Results and Discussion

Table 9: comparison of original images and processed images after GHE baseline and DHE algorithm

Original	GHE (Baseline)	DHE
 Contrast: 0.10, Entropy: 4.78, Brightness: 234.94	 Contrast: 0.36, Entropy %: 1.13, Brightness: 147.31, VIF: 0.68	 Contrast: 0.34, Entropy %: 1.13, Brightness: 177.97, VIF: 0.91
 Contrast: 0.19, Entropy: 6.64, Brightness: 189.64	 Contrast: 0.29, Entropy %: 1.05, Brightness: 118.30, VIF: 0.60	 Contrast: 0.29, Entropy %: 1.02, Brightness: 128.32, VIF: 0.59
 Contrast: 0.16, Entropy: 6.60, Brightness: 215.78	 Contrast: 0.30, Entropy %: 1.14, Brightness: 129.03, VIF: 0.46	 Contrast: 0.31, Entropy %: 1.11, Brightness: 135.06, VIF: 0.47
 Contrast: 0.05, Entropy: 5.64, Brightness: 233.30	 Contrast: 0.29, Entropy %: 1.32, Brightness: 128.25, VIF: 0.93	 Contrast: 0.31, Entropy %: 1.31, Brightness: 131.17, VIF: 0.86
 Contrast: 0.22, Entropy: 5.97, Brightness: 35.75	 Contrast: 0.28, Entropy %: 1.15, Brightness: 130.34, VIF: 0.83	 Contrast: 0.24, Entropy %: 1.07, Brightness: 113.90, VIF: 0.73

 Contrast: 0.24, Entropy: 6.72, Brightness: 53.88	 Contrast: 0.28, Entropy %: 1.08, Brightness: 128.11, VIF: 0.84	 Contrast: 0.22, Entropy %: 1.03, Brightness: 77.99, VIF: 0.79
 Contrast: 0.15, Entropy: 6.39, Brightness: 45.79	 Contrast: 0.29, Entropy %: 1.17, Brightness: 122.26, VIF: 0.90	 Contrast: 0.25, Entropy %: 1.15, Brightness: 90.74, VIF: 0.80
 Contrast: 0.20, Entropy: 6.79, Brightness: 51.38	 Contrast: 0.28, Entropy %: 1.10, Brightness: 126.83, VIF: 0.80	 Contrast: 0.29, Entropy %: 1.07, Brightness: 88.83, VIF: 0.69

For overexposed images (sample 01 to 04), the measurement metrics show that DHE significantly improves contrast and rebalances the brightness level of an overexposed image, compared to GHE, while maintaining similar VIF and entropy levels. In the sample 01 image, the signboard on the building rooftop is more visible than in the original image. However, DHE maintains the natural colour of the image, restore overexposure area. Unlike GHE, which can produce an unnatural, synthetic appearance, and leave some areas still overexposed.

For underexposed images (sample 05 to 08), the measurement metrics show that DHE increases the brightness level while also boosting contrast. However, sometimes result in less contrast compared to GHE in underexposed images. This happens because less dominant intensity ranges may receive even less span than their original range. For instance, in the sample08 image, the carpet texture in the dark area of the floor is less visible compared to the result with GHE. Overall, DHE is still better than GHE. The window blinds (sample06), window scenery (sample08), and balcony details (sample05) are areas where details with brighter light sources are better preserved.

In conclusion, DHE is capable of handling overexposed and underexposed images effectively, increasing visibility in low-contrast areas while preserving contrast in areas with sufficient detail when comparing with GHE. However, DHE has some disadvantages, including the complexity of splitting the histogram and the potential for inconsistent contrast enhancement, which can sometimes lead to inconsistent results. In certain cases, the method may not significantly improve contrast in underexposed areas.

Histogram Equalization with Maximum Intensity Coverage (HEMIC)

C. Y. Wong et al. (2016) proposed a method to enhance the contrast of an input image using a weighted sum-based strategy [3]. Their approach involves combining the input image with an interim equalized image by applying a weighting factor. This process is repeated in a search loop to find the optimal weighting factor, continuing until the number of filled histogram bins in the interim image is maximized.

Algorithm steps for HEMIC

1. Pre-processing with magnitude stretching

The pre-processing stage involves stretching the input RGB channels independently to their maximum possible ranges. This is done using the formula:

$$R(u, v) \leftarrow \frac{R(u, v) - R_{min}}{R_{max} - R_{min}} \times (L - 1)$$

Where R_{min} and R_{max} represent the minimum and maximum values of all pixels in the R-channel. The same procedure is applied to the green and blue channels. After stretching, the RGB image is converted to the HSI color space for enhancement. The H-channel and S-channel are left unchanged, as they do not directly influence the perceived contrast. In contrast, the human visual system is highly sensitive to changes in intensity, making the manipulation of the intensity channel particularly important.

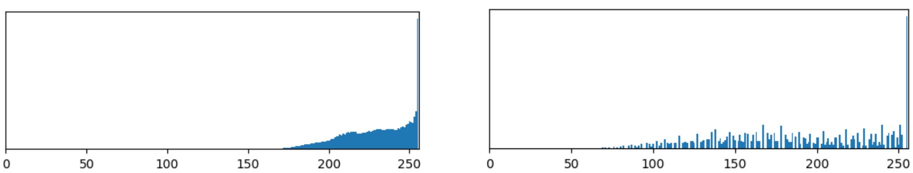


Figure 6: The histogram on the left represents the input image luminance channel, where most of the dark regions are empty. After stretching, as shown in the histogram on the right, the histogram spreads out.

2. Contrast Enhancement with maximum intensity

The pre-processed input image, denoted as I_{in} is subjected to histogram equalization, resulting in I_{eq}. An interim enhanced image is produced by taking a weighted sum of I_{in} and I_{eq} with a factor $\alpha \in [0, 1]$, as denoted by following.

$$I_{enh} = \alpha I_{in} + (1 - \alpha) I_{eq}$$

After that the number of empty bins in histogram of I_{enh} is determined as z_0. An objective function J is then formulated as

$$J = E\ x\left(1 - \frac{z_0}{L-1}\right)$$

Which is based on image entropy, as denoted by E, penalized by the number of empty histogram bins. High image contrast correlates with high entropy, and it is preferable to have fewer empty bins in the histogram.

Using the objective function J as a basis, the Golden Section algorithm is employed to conduct a search [4]. During this process, the value of the weighting factor α is iteratively adjusted until it converges to maximize the objective function. The interim image I_{enh} I-channel is then merged with the hue and saturation channels and converted back to the RGB space to produce the final output.

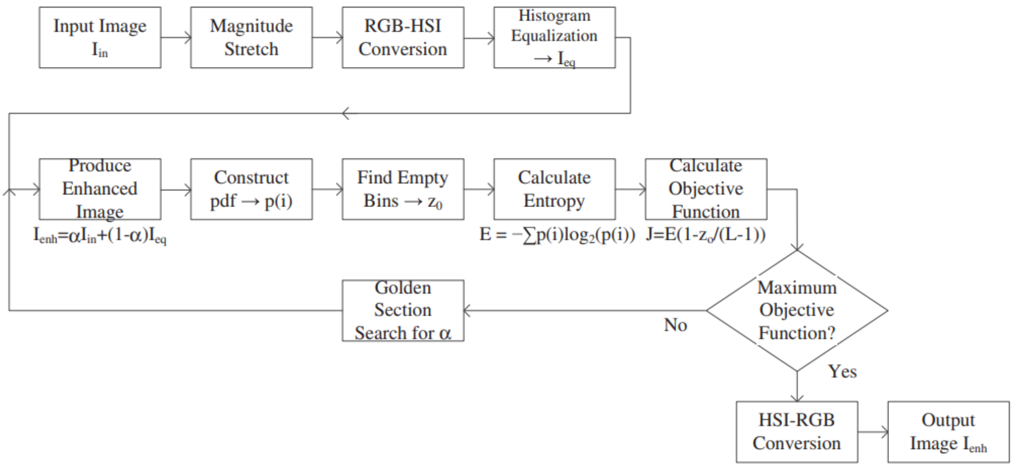


Figure 7: System block diagram of HEMIC

Results and Discussion

Table 10: comparison of original images and processed images after GHE baseline and HEMIC algorithm

Original	GHE (Baseline)	HEMIC
 Contrast: 0.10, Entropy: 4.78, Brightness: 234.94	 Contrast: 0.36, Entropy %: 1.13, Brightness: 147.31, VIF: 0.68	 Contrast: 0.26, Entropy %: 1.17, Brightness: 185.33, VIF: 1.00

Contrast: 0.19, Entropy: 6.64,
Brightness: 189.64

Contrast: 0.29, Entropy %: 1.05,
Brightness: 118.30, VIF: 0.60

Contrast: 0.24, Entropy %: 1.10,
Brightness: 157.02, VIF: 0.82

Contrast: 0.16, Entropy: 6.60,
Brightness: 215.78

Contrast: 0.30, Entropy %: 1.14,
Brightness: 129.03, VIF: 0.46

Contrast: 0.23, Entropy %: 1.13,
Brightness: 172.48, VIF: 0.67

Contrast: 0.05, Entropy: 5.64,
Brightness: 233.30

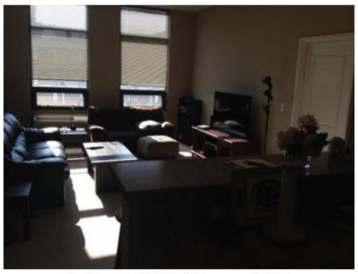
Contrast: 0.29, Entropy %: 1.32,
Brightness: 128.25, VIF: 0.93

Contrast: 0.22, Entropy %: 1.33,
Brightness: 161.29, VIF: 1.44

Contrast: 0.22, Entropy: 5.97,
Brightness: 35.75

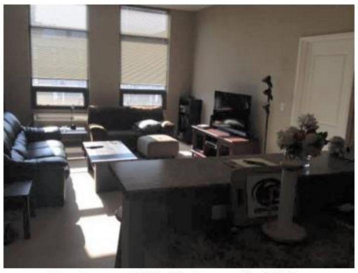
Contrast: 0.28, Entropy %: 1.15,
Brightness: 130.34, VIF: 0.83

Contrast: 0.24, Entropy %: 1.13,
Brightness: 76.86, VIF: 0.98



Contrast: 0.24, Entropy: 6.72,
Brightness: 53.88

Contrast: 0.28, Entropy %: 1.08,
Brightness: 128.11, VIF: 0.84



Contrast: 0.25, Entropy %: 1.07,
Brightness: 84.06, VIF: 0.95

Figure ?: HE and HEMIC processed images. Row 1-8 shows sample image 01 to 08

Sample image 01 (first row) and image 03 show overexposed views of buildings from different angles. Histogram Equalization (HE) tends to spread the concentrated high-intensity region of the histogram across the full range of [0, 255]. As a result, many dark patches appear, and enhanced details may not be clearly visible. HEMIC performs well in maintaining details, such as the tree in the bottom right corner and the Chinese character sign on top of the white building in sample image 01. It also brings out the texture of the buildings and the foreground hilly terrain with high contrast in sample image 03. This observation is supported by the high entropy values. Although HEMIC achieves stronger contrast compared to the original images, it also exhibits overall saturated colours, possibly due to the colour channel stretching operation.

For sample image 02, HEMIC provides overall enhancement, improving contrast, detail, and texture without compromising the natural appearance. It offers a good balance, making it visually appealing and closer to the original in terms of content fidelity.

Sample image 04 appears washed out, with very low contrast. The details, especially in the brighter areas, are difficult to distinguish. The overall scene lacks depth, making it hard to perceive individual elements clearly. Visually, HEMIC provides moderate enhancement in contrast and detail. It improves visibility over the original without introducing harsh artifacts, maintaining a relatively natural look. While it is not as striking as HE in terms of contrast, the colour saturation is high due to the stretched colour channels.

Sample images 05 to 08 are underexposed indoor shots. HE lightens the details in the dark regions of the images, but the bright areas become overexposed, causing the details to be lost. HEMIC results in more balanced images, where details in both dark and light regions are visible, providing a high VIF score. In these cases, HEMIC produces a slightly dimmer overall result but retains as much information as HE, as indicated by the entropy values. The colour saturation did not change, likely because the minimum and maximum intensity values of the original images colour channel were already 0 and 255, respectively, so colour stretching had no effect.

Best HE algorithm model

Metrics of each HE averaged over 8 images:

Table 11: Evaluation results of all HE models, excluding visual analysis by team members

	Original	**HE**	**DHE**	**CLAHE**	**HEMIC**
VIF	1	0.757	0.731	0.916	0.973
Relative entropy	1	1.138	1.106	1.140	1.138
Brightness	135.560	128.802	118.000	132.388	124.508
Contrast	0.165	0.296	0.280	0.214	0.232

Compared with HE and DHE, CLAHE and HEMIC maintained a very high VIF score across 8 different images, indicating that these two HE algorithms can preserve the visual information in the original image under various exposure scenarios, as perceived by the human eye.

During HE execution, some histogram bins of different intensity values might be merged into the same bin, reducing the image's entropy, or in other words, decreasing the amount of information retained in the image. HE, CLAHE, and HEMIC all performed well in this metric, indicating their ability to preserve the texture and details of the original image. In our work, most of our algorithms apply to the converted luminance Y-channels, but we calculate the average entropy across the R, G, and B channels, which is why the relative entropy compared to the original image is greater than one. The numbers here are used to compare the amplitude of each HE algorithm to determine which one works best in terms of preserving information.

Regarding brightness, CLAHE is the best at preserving the brightness of the original image, likely due to its method of equalizing localized histograms. HEMIC, on the other hand, generates dimmer images when the input is underexposed, which may explain its lower brightness preservation.

Lastly, we observe that all the HE algorithms increased the contrast of the original image. HE increased the contrast to the highest degree, but it produced harsh textures that are not appealing to the human eye. DHE offers slight improvement, but CLAHE and HEMIC excel at maintaining moderate contrast with clear and natural textures.

Best HE Image Visual Analysis voting

Table 12: Original image and enhanced images from various HE algorithms

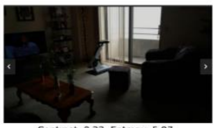
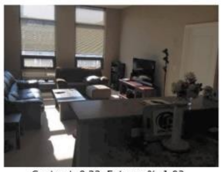
Original	GHE (Baseline)	CLAHE	DHE	HEMIC
 Contrast: 0.10, Entropy: 4.78, Brightness: 234.94	 Contrast: 0.36, Entropy %: 1.13, Brightness: 147.31, VIF: 0.68	 Contrast: 0.21, Entropy %: 1.17, Brightness: 209.17, VIF: 1.01	 Contrast: 0.34, Entropy %: 1.13, Brightness: 177.97, VIF: 0.91	 Contrast: 0.26, Entropy %: 1.17, Brightness: 185.33, VIF: 1.00
 Contrast: 0.19, Entropy: 6.64, Brightness: 189.64	 Contrast: 0.29, Entropy %: 1.05, Brightness: 118.30, VIF: 0.60	 Contrast: 0.22, Entropy %: 1.09, Brightness: 172.63, VIF: 0.68	 Contrast: 0.29, Entropy %: 1.02, Brightness: 128.32, VIF: 0.59	 Contrast: 0.24, Entropy %: 1.10, Brightness: 157.02, VIF: 0.82
 Contrast: 0.16, Entropy: 6.60, Brightness: 215.78	 Contrast: 0.30, Entropy %: 1.14, Brightness: 129.03, VIF: 0.46	 Contrast: 0.26, Entropy %: 1.14, Brightness: 179.50, VIF: 0.72	 Contrast: 0.31, Entropy %: 1.11, Brightness: 135.06, VIF: 0.47	 Contrast: 0.23, Entropy %: 1.13, Brightness: 172.48, VIF: 0.67
 Contrast: 0.05, Entropy: 5.64, Brightness: 233.30	 Contrast: 0.29, Entropy %: 1.32, Brightness: 128.25, VIF: 0.93	 Contrast: 0.13, Entropy %: 1.22, Brightness: 204.13, VIF: 0.98	 Contrast: 0.31, Entropy %: 1.31, Brightness: 131.17, VIF: 0.86	 Contrast: 0.22, Entropy %: 1.33, Brightness: 161.29, VIF: 1.44
 Contrast: 0.22, Entropy: 5.97, Brightness: 35.75	 Contrast: 0.28, Entropy %: 1.15, Brightness: 130.34, VIF: 0.83	 Contrast: 0.24, Entropy %: 1.20, Brightness: 63.36, VIF: 1.03	 Contrast: 0.24, Entropy %: 1.07, Brightness: 113.90, VIF: 0.73	 Contrast: 0.24, Entropy %: 1.13, Brightness: 76.86, VIF: 0.98
 Contrast: 0.24, Entropy: 6.72, Brightness: 53.88	 Contrast: 0.28, Entropy %: 1.08, Brightness: 128.11, VIF: 0.84	 Contrast: 0.24, Entropy %: 1.10, Brightness: 74.83, VIF: 1.01	 Contrast: 0.22, Entropy %: 1.03, Brightness: 77.99, VIF: 0.79	 Contrast: 0.25, Entropy %: 1.07, Brightness: 84.06, VIF: 0.95
 Contrast: 0.15, Entropy: 6.39, Brightness: 45.79	 Contrast: 0.29, Entropy %: 1.17, Brightness: 122.26, VIF: 0.90	 Contrast: 0.18, Entropy %: 1.14, Brightness: 77.00, VIF: 0.98	 Contrast: 0.25, Entropy %: 1.15, Brightness: 90.74, VIF: 0.80	 Contrast: 0.19, Entropy %: 1.13, Brightness: 76.90, VIF: 0.97
 Contrast: 0.20, Entropy: 6.79, Brightness: 51.38	 Contrast: 0.28, Entropy %: 1.10, Brightness: 126.83, VIF: 0.80	 Contrast: 0.23, Entropy %: 1.10, Brightness: 78.48, VIF: 0.92	 Contrast: 0.29, Entropy %: 1.07, Brightness: 88.83, VIF: 0.69	 Contrast: 0.23, Entropy %: 1.08, Brightness: 82.14, VIF: 0.95

Table 13: Visual Analysis votes by all team members for the best HE algorithm for each images

Image	Ming Yuan	Seik Man	Timothy	Lehan	Chen Fei	Winner HE
sample01 (building)	HEMIC	HEMIC	HEMIC	HEMIC	HEMIC	HEMIC
sample02 (cat)	CLAHE	CLAHE	CLAHE	DHE	DHE	CLAHE
sample03 (HDB)	DHE	CLAHE	CLAHE	CLAHE	DHE	CLAHE
sample04 (trees)	HEMIC	HEMIC	HEMIC	DHE	HEMIC	HEMIC
sample05 (balcony)	DHE	CLAHE	CLAHE	CLAHE	CLAHE	CLAHE
sample06 (living hall)	CLAHE	CLAHE	CLAHE	CLAHE	CLAHE	CLAHE
sample07 (room)	HEMIC	HEMIC	HEMIC	HEMIC	HEMIC	HEMIC
sample08 (bedroom with window)	CLAHE	CLAHE	CLAHE	CLAHE	CLAHE	CLAHE

From our table results above, there are 3 images where HEMIC have the best votes and 5 images where CLAHE has the best votes. We deduce that the CLAHE algorithm is the best model for the 8 images provided to us. Although CLAHE has the lowest average absolute contrast over 8 images when compared to other enhancement models namely HEMIC and DHE, it has the highest absolute brightness and a relatively high VIF score. This could imply that CLAHE is good at increasing the brightness of dark images and decreasing the brightness of overexposed images. This allows the images to be more homogeneous where pixel intensities are more uniform across the image, which can potentially explain why the average contrast of CLAHE is the lowest.

For sample images such as 1, 6, 7 and 8, we see that all members vote for the same HE algorithm while the rest of the sample images, we see varying votes. The difference in votes can be due to visual perception being subjective, and individuals have varying opinions about what constitutes an image with better contrast.

Conclusion

In this report, we compared the performance of the baseline Global Histogram Equilization (GHE) algorithm with other enhanced GHE algorithm such as the Contrast Limited Adaptive Histogram Equalization (CLAHE), Dynamic Histogram Equalization (DHE) and Histogram Equalization with Maximum Intensity Coverage (HEMIC) algorithms over 8 sample images. The success indicators used are Visual Analysis by team members, relative Entropy, Visual Information Fidelity, Absolute Contrast and Absolute Brightness. Our team deduced that CLAHE is the best model. Nevertheless, the best model might change if other images were used instead of the 8 given sample images. Hence, to increase the accuracy of which HE enhancement algorithm is the best suited for enhancing images, more numbers of sample images can be provided for the team to conduct analysis for the team determine the best HE enhancement algorithms or what HE enhancement algorithm is suited for what kind of images.

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Can remove later

Upon analysing the histogram data in table 2, it is evident that the histograms for all eight images exhibit a more even and widespread range of pixel distribution. However, certain sections of the histograms remain densely populated. For instance, bright images such as enhanced images 1, 2, 3, and 4 still have a significant concentration of pixels in the lower value range of 0 to 100. Darker images like 5, 6, 7, and 8 continue to show a high pixel density in the upper value range of 200 to 255 after GHE algorithm. This indicates that the Global Histogram Equalization (GHE) algorithm is limited in its ability to adjust the overall brightness of the images. Despite the GHE image enhancement process, bright images remain relatively bright, and dark images retain their darker tones. This is because the GHE algorithm works by redistributing the pixel intensities based on the CDF of the entire image and might not adjust the brightness effectively in certain areas of the image.

Enhanced images 2 and 4 did not have a pixel value range of 255 as shown in table 2. This could be because original images of both images have very low dynamic range where majority of the image pixels are high. The GHE algorithm is unable to stretch the high pixel values from the original images across the entire pixel value range of 255.

Upon reviewing the processed images, it is evident that enhanced images 1, 2, 3, and 4 exhibit increased contrast but also display a more pixelated and noisier appearance with outlier pixels following the GHE enhancement. This suggests that the contrast levels for these enhanced images are excessively high when the pixel values are redistributed, leading to information loss and making the images less visually appealing. In the case of enhanced images 5 and 6, the brightness is elevated to the point where the colours appear faded, and the contrast is so intense that the images become pixelated.

For enhanced images 7 and 8, the bright areas, such as the light bulb in image 7 and the scene outside the window in image 8, are over-brightened and over-contrasted, causing the semantics of the light bulb and the objects outside the window to diminish significantly. This results in a loss of information, as the bright objects are no longer clearly visible in the images.

As observed in Table 2 there is a general decrease in brightness and an increase in contrast in the GHE-enhanced images. The relative entropy and VIF for the original images are both 1, as they are compared against themselves. Following GHE enhancement, the relative entropy increases, which aligns with expectations since Table 3 indicates that the histograms of the eight images become more evenly distributed post-GHE enhancement. However, the VIF drops below 1 after GHE enhancement, likely due to the flaws in the enhanced images, as discussed in the preceding paragraphs.

Pros and Cons of GHE algorithm

Pros

As seen in the output enhanced images in table 3, the contrast of most images has generally improved, and the details of most images can be seen more clearly. This can be seen from the histogram of the enhanced images where the pixel image values are more evenly distributed, and the range of pixel values has increased compared to that of the original images.

Since the algorithm will convert images to greyscale before doing the redistribution of pixel values, this algorithm is applicable to both coloured and greyscale images and can be widely used in different applications. The algorithm is relatively straight forward and easy to implement, making it efficient.

Cons

Looking at table 2, we can see that the range of pixel values of histogram of the enhanced images are not 255 for all images, such as for sample image 2 and 4. The GHE algorithm might be unable to spread the pixel values of the images across the maximum range if the original images have small dynamic range.

Moreover, GHE algorithm can overexpose the parts of the images which leads to loss of information, as seen from enhanced image 5 where the colours of the entire image were washed out. Over enhancements are also seen in images such as enhanced image 5 where the sofa area and enhanced image 6 where the table, are pixelated.

Additionally, GHE do not preserve local contrast of the image as it does not differentiate between local variations in brightness or contrast, leading to loss of information in certain areas of the image. In the original image of image 8, the area in the room is dark while the area outside the window bright. After the GHE algorithm is applied, the area outside the window of the enhanced image is overexposed and looks mainly white while in the original image, we can see a clearer view of the balcony outside the window. Such issue is also seen in enhanced images 5 and 6 where the semantics and colours of the area outside the window becomes less obvious than their original images. This shows that GHE has limited control for the image enhancement as it focuses on global contrast, leading to unsatisfactory results at certain parts of the images.

Since the GHE has room for improvement, we will explore other HE algorithms which are modifications of the GHE algorithm which aims to enhance the GHE algorithm. We will evaluate the results of the performance of those other HE algorithms on the 8 images to determine if they are doing better or worse than the GHE baseline algorithm.