AI 6121- Computer Vision Assignment 1

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Abstract
In the fields of computer vision, histograms are used to capture the frequency of the pixel intensity values and provide a deeper insight into the image's distribution at the intensity levels. Histogram Equalization (HE) is a common technique used to redistribute the image's intensity range if it gets too concentrated within the intensity range. Another feature of HE is applying global contrast to allow the region with lower contrast to gain higher contrast to be more visible. In this assignment, our team will introduce the HE algorithm implemented in Python. Secondly, to discuss its pros and cons based on our implemented HE. Lastly, explore the possible improvements to the basic HE by CLAHE.

1. Introduction

Histogram Equalization (HE) is commonly used for the grey-level transformation in image processing. The core principle of HE is operated by evenly redistributing the common pixel values and establishing a linear trend in the image's cumulative distribution function (CDF).

In order to reduce the imbalance in the distribution, a flattening approach has been adopted to perform on the pixel intensity range [0,255]. It will significantly increase the contrast with the initially low-contrast region in the original image since the global contrast has increased.

Below are the drill-down steps on the derivation of the HE algorithm. Let's assume that there is a grayscale image with a pixel range [0, L-1]. The max intensity level = 256 in an image.Pixel range =[0,255]

The formula of the Probability Density Function (PDF) is denoted as :

$$P_k = \sum_{j=0}^{k} N_j$$

Figure 1: Formula on Probability Density Function (PDF)

After dividing by W*H, we get the Cumulative Density Function (CDF) of the image:

$$P_r(r_k) = \sum_{j=0}^{k} * \frac{N_j}{W * H} = \sum_{j=0}^{k} P_j$$

Figure 2: Formula on Cumulative Density Function (CDF)

After applying HE, multiply the range(L-1) to get the average number of pixels falling into each bin. The HE function:

$$s_k = (L-1)\sum_{j=0}^{k} P_j$$

Figure 3: Formula on HE function.

Therefore, implementing the HE will enhance the contrast and create a more visually appealing image.

a. Data Understanding

In this section, to understand the image better, our team has studied all the images, and the common attribute of the sample images have in common is that they are colour images. The only difference is that some sample images are too bright compared to the others, and we classify them as overexposed. While the other is too dark, we will classify them as underexposed. Both different classifications are evenly distributed. Below Figure 4 are the 2 sample images, which displayed the overexposed (sample 1) and underexposed images (sample 6).

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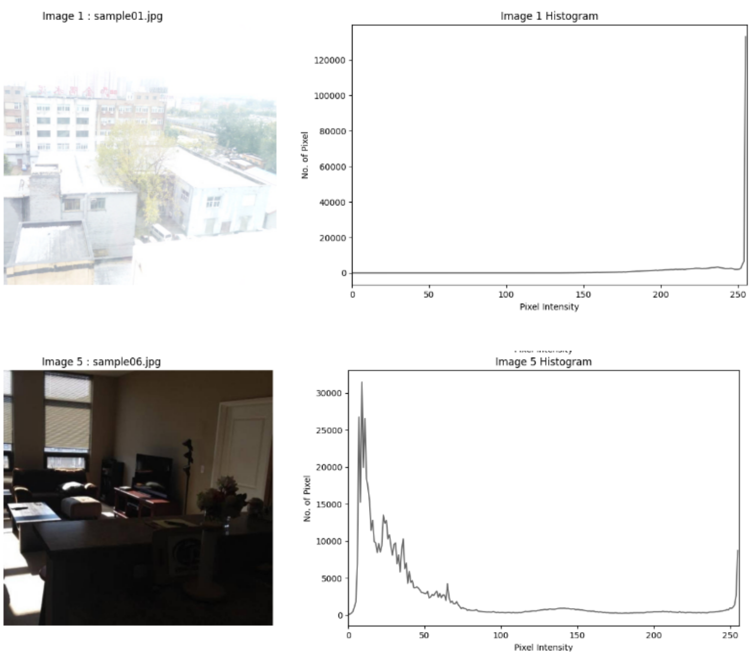


Figure 4. Sample image with histogram (top :Overexposure(Bright) image , bottom: Underexposure(dark) image)

Based on the result gathered in Figure 4, sample 1 is more clustered at the high pixel intensity (right side of the histogram). While sample 6 tends to be clustered more to the low pixel intensity (left side of the histogram).

It suggested that enhancement of images is required by HE on the colour images. Therefore, besides the Basic HE, our team will adopt the following colour space HE technique to experiment and perform image processing by enhancing the contrast and making it more visible. (Refer to the appendix under All Sample images generated for the Data Understanding Histogram.)

2. Histogram Equalization (HE) (Task 1)

The image processing domain is not only applicable to grayscale images but also expands the domain to colour images as well. Therefore, in this section of the assignment, it will discuss the HE technique, which has been applied to the individual channels and treat them as grayscale images to allow better easy implementation.

Our team has chosen the Basic HE and the colour space: RGB (R, G, B channels) and YUV (Y channel) to assess the effects. The colour space is being chosen to analyse mainly because the sample image is all colour images, and they are prevalent in image processing. To ensure the accuracy of the HE implementation, our team will compare it with the result obtained from the OpenCV "cv2.equalizeHist()" function. The result will give us a better understanding of the efficiency and applicability of HE in various image colour spaces.

a. Basic Histogram Equalization (HE)

Basic histogram equalization (HE) is an image enhancement technique in computer vision. It enhances an image by redistributing the pixel intensity values in the image's histogram (R. Chen, 2023). The steps of a basic histogram equalization algorithm:

1. **Compute the histogram**: Compute the histogram of the original image.
2. **Cumulative Distribution Function (CDF)**: Calculate the CDF from the histogram.
3. **Normalize the CDF values**: Normalize the CDF values by dividing each value in the histogram by the total number of pixels in the image.
4. **Histogram equalization transformation**: Map the original pixel intensity values to the new values using the CDF.
5. **Apply the transformation:** Replace the original pixel intensity values with the new values.
6. **Output image:** Plot the enhanced image.

Original Images and Histogram (Sample 1):

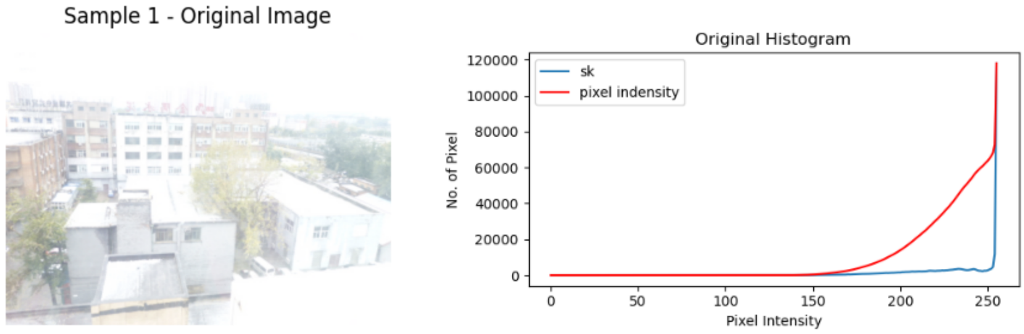


Figure 5 - Original Image and Histogram of Sample 1

Original Image and Histogram (Sample 6):

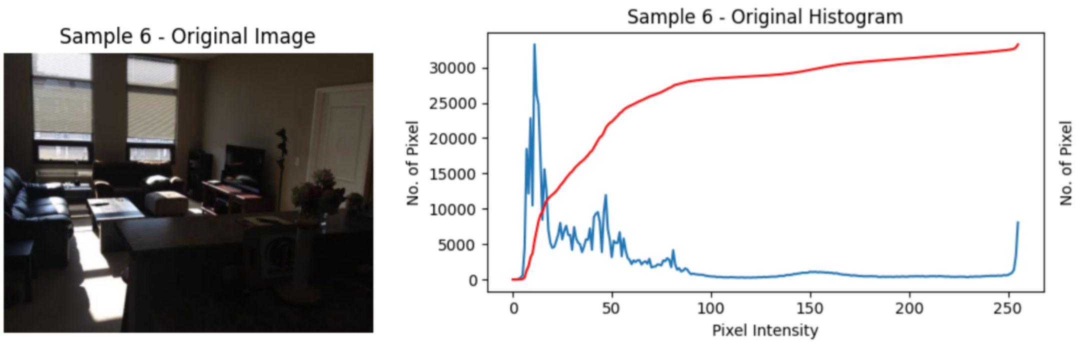


Figure 6 - Original Image and Histogram of Sample 6

After implementing Basic HE and Image and Histogram (Sample 1):

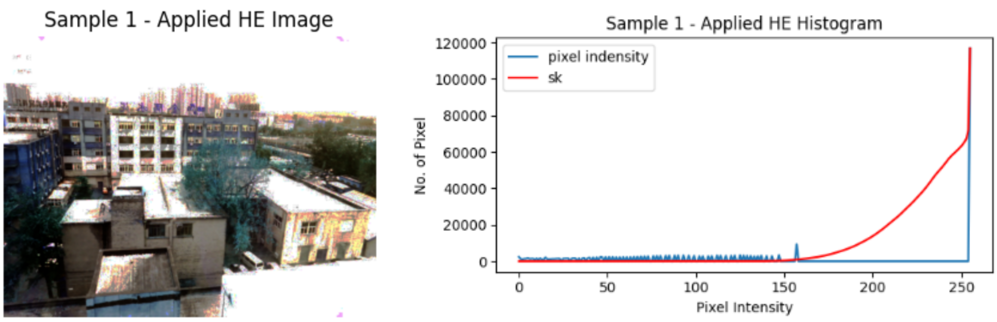


Figure 7 - Applied Basic HE Image and Histogram of Sample 1

Applied Basic HE Image and Histogram (Sample 6):

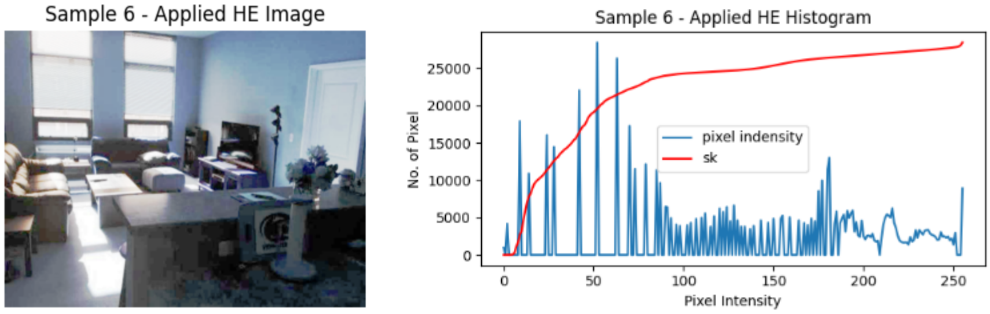


Figure 8 - Applied Basic HE Image and Histogram of Sample 6

As seen in Figure 5, the original image of Sample 1 is extremely over-saturated. After basic HE, as seen in Figure 7, the applied image of Sample 1 is now darker and less over-saturated. However, since the transformation is applied to the entire image, there are still some areas of the image (i.e. the sky) that are still over-saturated.

As seen in Figure 6, the original image of Sample 6 is extremely dark and low-lit. After basic HE, as seen in Figure 8, the applied image of Sample 6 is brighter. However, since the transformation does not take into account different colour channels, the image is now leaning towards a blue hue, making it look unnatural.

Hence, basic HE is a simple method to enhance an image overall, but it may not be the ideal transformation method since it does not take into account features of the image.

b. Colour Space: Red Green Blue Channel (RGB)

The primary colours or channels in the colour model are R-Red, G-Green and B-Blue, or RGB channels. It is an addictive model which enables the creation of different hues by merging the light intensities. Furthermore, as a role of the receptor of the human eye, the colour is easily identified by humans (wikipedia, 2022).

Since all sample images are in colour, no conversion of colour to grayscale or vice versa is required in this RGB HE implementation. Cumulative Distribution Probability (CDF) and normalization have been used as the mathematics behind to derive the result.

Furthermore, under the implementation, HE was individually implemented in each channel in R, G and B. However, to get the best optimal balance or contrast, there is a need to combine the 3 channels to avoid having an imbalance of colour or even distortion within the image. The OpenCV function "cv2.equalizeHist()" is also being used to validate the accuracy of the implemented RGB HE.

<u>Original Images RGB:</u>

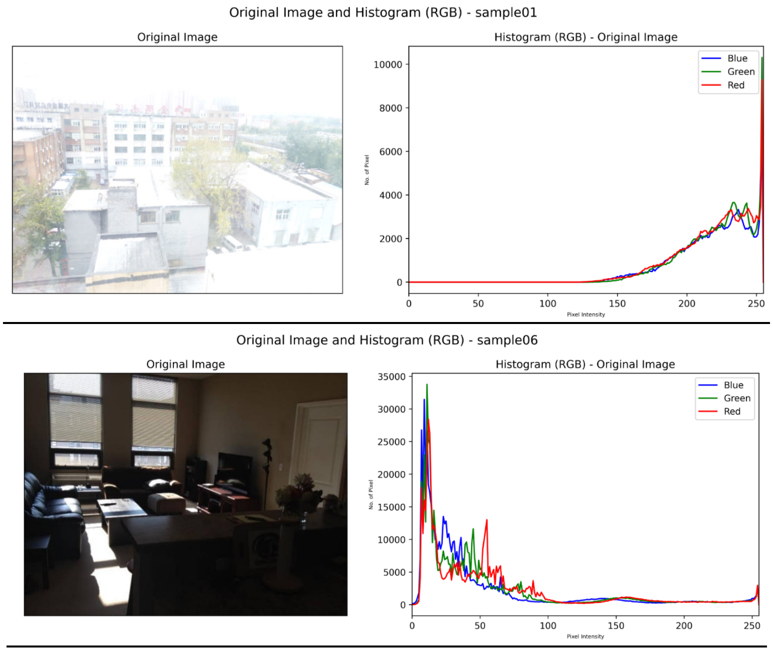


Figure 9. Original image (RGB) - Left (Sample 01), Right (Sample06)

<u>After implementing RGB HE, The extra RGB line denotes the SK line</u>

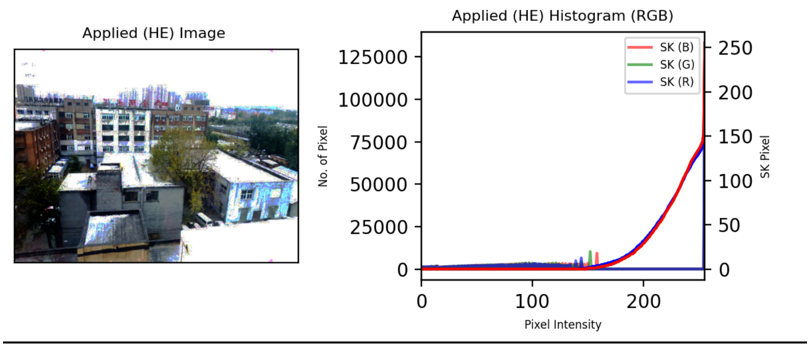
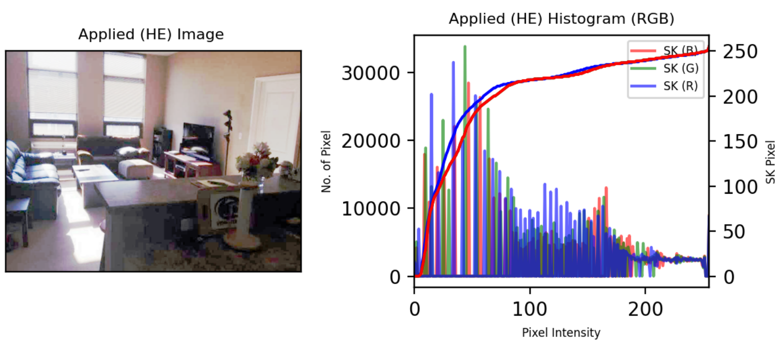


Figure 10: After implementing RGB HE - Left (Sample 01), Right (Sample06)



<u>After implementing RGB, HE is using cv2.equalizeHist()</u>

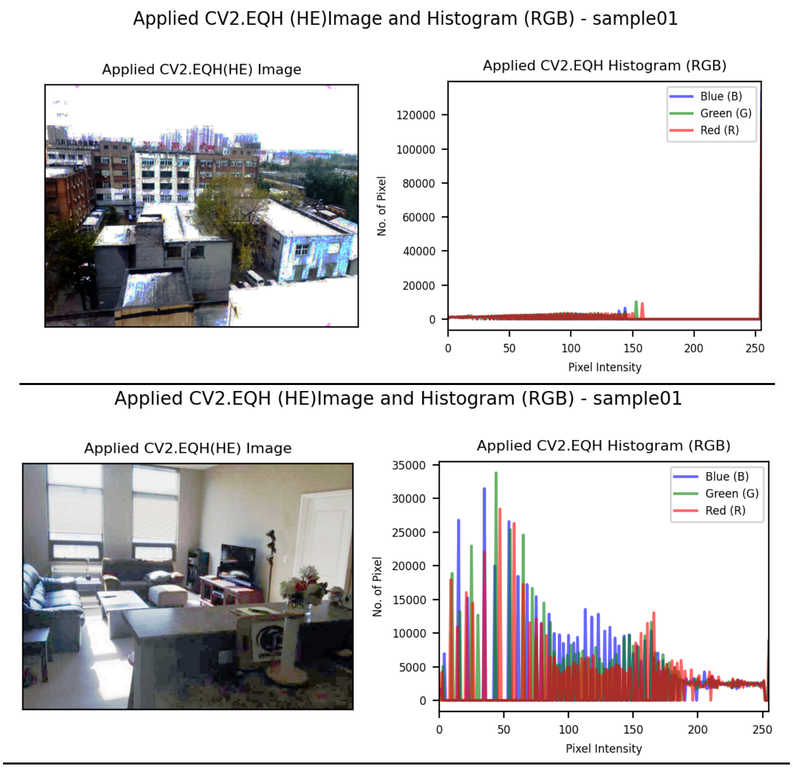


Figure 11. After implemented RGB HE using CV2.equalizerHist() - Left (Sample 01) , Right (Sample06)

Our team has gathered some observations from Figure 4. Similar behaviors with data understanding have been detected where the 3 channels are more centralized on the taller on left side of the chart for overexposure(bright) images with high pixel intensity. In contrast, the underexposure (darker) images are centralized on the right side and taller of the chart with lower pixel intensity. Furthermore, blue and green are more dominant in this chart than red, possibly due to the colours found in the sample image.

Secondly, from the enhanced image after the HE implementation in RBG, in Figure 10 and Figure 11 for sample 6, we can identify more items, such as a kitchen bench and a board located on the bench, which we cannot easily identify in the original images due to low contrast in the under-exposure image.

Lastly, our team can conclude that our implemented RGB HE is accurate if it is validated with the "cv2.equalisationHist()" function, as they yield the same result. In our own implemented RGB HE, CDF and normalization have been adopted to enhance the images to provide more visibility.

Original Applied HE RGB

Figure 12. Original VS Applied HE RGB (Sample1)

However, some form of colour distortion (circled in red) has been detected, in the sample 1 output image in Figure 12, there is cyan colour being shown in windows and walls. This might suggest that as each channel is individually calculated and transformed based on intensity level, it may cause the RGB HE to have a distortion in colours or change in colours that give off an unnatural look.

c. Colour Space: YUV Channel

YUV is the one widely used colour space, also known as YCbCr. Y denotes brightness, U denotes blue projection, and V denotes red projection. YUV is a mathematical encoding image space. It incorporates both brightness and colours. YUV contains 'brightness', 'Blue projection' and 'red projection'. Due to the single brightness channel, YUV is the most helpful colour space in generating grayscale images.

To expand the grey image domain to the colour image, we treat a single channel as a grey image and implement the HE. In this part, we have implemented the HE function by using Python. Similarly, our team compared our results with the OpenCV "cv2.equalizeHist()" function to prove the function's accuracy. Hence, the results can be adopted to analyse the efficiency with different image colour spaces.

This work analyses the effects by applying HE to RGB (R, G, B channel) and YUV(Y channel) image space. Similarly, comparing Figure 8. the histogram of our HE algorithm and the OpenCV histogram indicates our algorithm is accurate.

Original Images YUV:

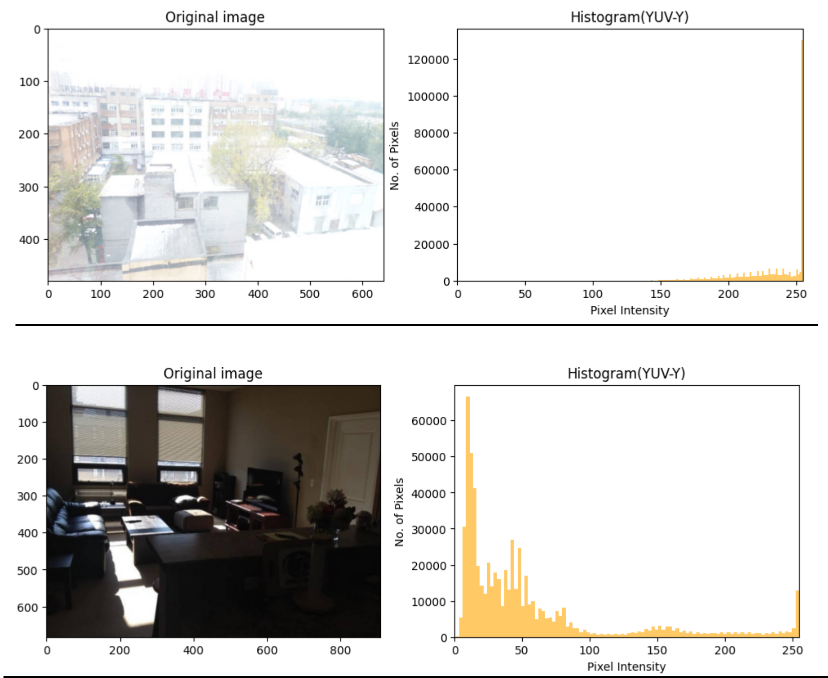


Figure 13. Original image (RGB) - Left (Sample 01), Right (Sample06)

After implementing YUV HE, The extra line denotes the S.K. line.

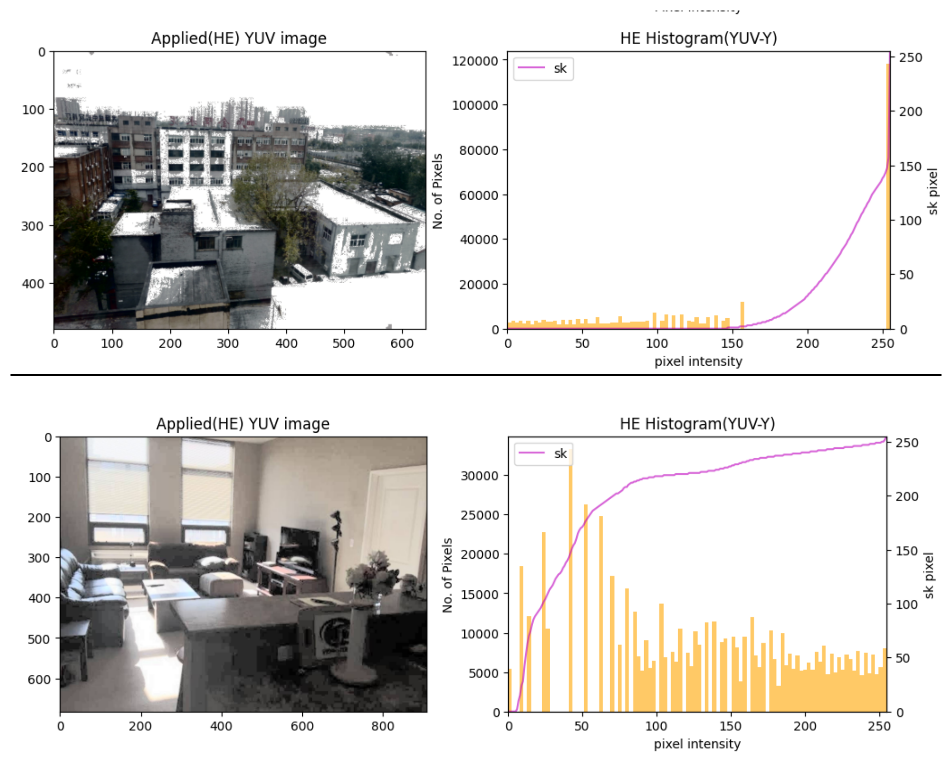


Figure 14. After implementing YUV HE - Left (Sample 01), Right (Sample06)

After implementing YUV, HE is using cv2.equalizeHist()

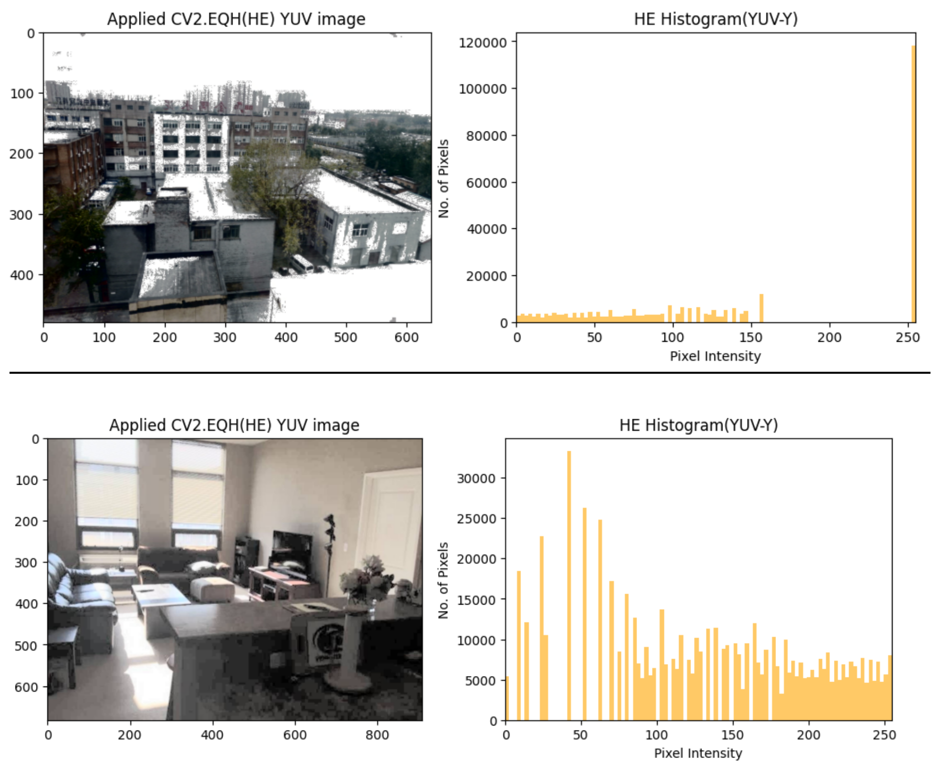


Figure 14. After implemented YUV HE using CV2.equalizerHist() - Left (Sample 01) , Right (Sample06)

The benefit of the YUV image is that it has a single luma channel to control the brightness of the image. Similar to the RGB image and data understanding plot, the histogram of the darker image is more centralized on the left side, and the histogram of the brighter image is towards the right side.

From our observation from Figure 13 and Figure 14, after applying the HE to YUV, the same result was obtained when experimenting with OpenCV "cv2.equalizeHist()", which proved the accuracy of our implemented HE function.

Since our team only applied HE to the luma channel of the YUV image, which is to enhance the brightness, it did not cause any colour distortion. However, specific details may become overly prominent as pixel intensities have redistributed, resulting in the loss of subtle brightness variations.

3. The Pros and Cons (Task 2)

Our team will examine the pros and cons based on the above-implemented HE in this section.

a. The Pros

Below are the identified pros:

- **Improved Contrast** (N., 2023): Using histogram equalization increases the contrast in an image, thus making an image with poor contrast sharper and bringing out the details in an image. Firstly, this is true for basic histogram equalization, especially when an image has poor contrast. Secondly, this is true for RGB, as equalizing histograms of each colour separately improves the contrast of particular colours within the image. Thirdly, this is true for YUV, as histogram equalization is done to the brightness channel, which improves image contrast while allowing an image to maintain its inherent colour palette. From the experiments conducted, our team observed that the contrasts of the image were enhanced when the HE was applied, and the images were more visible when compared to the original images.
  For example, from sample06, we can identify the items located on the table after applying HE mainly because the redistribution of the intensities enhances the image contrast. However, without the HE implementation, we cannot even know there is a kitchen bench present in the image. Therefore, HE makes the enhanced image more clearer as compared to the original images.
- **Simple Implementation** (N., 2023): Simple Implementation (N., 2023): Histogram equalization can be done without any heavy complex computations. The basic histogram equalization is the simplest technique to execute, and consecutively, RGB and then YUV. Therefore, it is simple to implement in our team's experiments space (Basic HE, RGB, and YUV). Reverting back to the original is easy since it is 1-1 mapping due to the simple transformation that it adopted. Information on the original image will be retained and well preserved. With this fast and budget-friendly method, it have been widely used as a tool for image enhancement in the current world today.
- **Flexibility in Enhancement:** Using histogram equalization means that there is flexibility in whether or not enhancement is applied to the entire image or certain features of an image. Firstly, basic histogram equalization allows for enhancement to the entire image, which can be used as an easy fix for an image. Secondly, RGB allows for selective enhancement of specific colour channels, which can be useful when one wants to emphasize a specific colour over another colour.
- **Absence of Colour Mixing:** Certain histogram equalization techniques allow for colour information not to be mixed between channels. Firstly, this applies to RGB. Since each colour channel is processed separately, colour information is not mixed between channels. Secondly, this applies to YUV. The histogram equalization is performed on the Y channel; the U and V channels, which contain the colour information, are not mixed. The absence of colour mixing helps to maintain the original colour relationships of an image.

b. The Cons

Below are the identified cons:

- **Increased Noise:** Under the histogram equalizer, the contrast of the histogram in an image is uniformly adjusted as a whole and not selective, thus leading to an increase in noise. It poses a challenge in identifying noise or information. In our experiment, HE in RGB is applied to 3 channels while the YUV is applied to the luma channel. The core concept of HE to redistribute the pixels in order to enhance the images will subsequently increase the noise and degrade the quality of the images. This is able to be illustrated in sample 8; after the HE is included in RGB, the information outside the windows is lost due to the increase in contrast.

- **Information Loss** (Linkedin, 2023): Since histogram equalization stretches the pixel intensity levels, there may be information loss, such as an image's variations and details. Firstly, this applies to basic histogram equalization. Secondly, this applies to RGB. Since colour channels can be correlated, separating them and removing this correlation can lead to information loss, as seen through an image's non-cohesive colour palette. Thirdly, this applies to YUV. Histogram equalization applied to the Y channel does not enhance colour contrast through separate colour channels, which can lead to information loss, such as an image with a low saturation.
- **Lack of Context:** Histogram equalization does not take into account the content or context of an image, such as lighting conditions. Thus, it can lead to an image that looks over-edited as it can be over-saturated or under-saturated and an increase in noise. This mostly affects basic histogram equalization, although it can affect RGB and YUV to a lesser degree.
- **Over-dependence on the histogram:** An image's initial histogram affects how well the image can be enhanced. Thus, if the initial histogram has skewed values or anomalies, the histogram equalization method may not create the intended results. This affects all three methods since they all use a histogram.
- **Limited Enhancement Features:** Histogram equalization provides few enhancement features. This affects basic histogram equalization the most since there is no way to adjust the enhancement features, such as the contrast of an image. There are more enhancement features in RGB since one can choose the colour channel, and subsequently in YUV too.
- **Flawed Colour Preservation** (Linkedin, 2023): Applying histogram equalization to colour images can distort the image's original colour balance and saturation. Firstly, this applies to basic histogram equalization since there is no separation of colour channels. Secondly, this applies to RGB because although there is separation of colour channels, it still mixes the brightness and colour information in each channel, which can lead to distorted colours.
- **Limitations in Using Colour Channels** (Linkedin, 2023): There may be limitations to using histogram equalization when using colour channels. Firstly, this affects RGB. Since RGB uses colour channels, it can cause colour imbalance in which certain colours become more dominant than others, causing an unnatural-looking image. Secondly, this affects YUV. Since YUV uses brightness, there are limitations to the enhancements that can be made in specific colour channels.

c. Results Evaluation

Based on the implemented basic HE into RGB and YUV experiments on all the sample images provided, these 3 techniques have pros and cons. In observing the sample 2 image on the cat image and sample 4 on the trees, images generated by HE RGB seem pixelated. At the same time, YUV provides better image quality with real colour. From sample 5, the table's colour in RGB HE has changed to cyan, but basic HE and YUV remain the same as the original, which can conclude RGB HE will cause colour change and distortion.

Furthermore, our team also discovered that RGB HE will generate a false impression of the day when the image is taken based on sample 7. For both HE and YUV, the images are warm in colour, allowing us to think it is taken during the evening. But for RGB, it is brighter than the other 2, giving the impression the image was taken during a sunny afternoon. Thus, based on these discoveries, we can conclude that YUV is the most appropriate selection within these experiment techniques.

To sum it up, histogram equalization is a useful tool in improving image contrast. Basic histogram equalization is a simple way to improve an image with poor contrast. However, it comes with the most disadvantages, such as information loss and limited enhancement features. Consequently, histogram equalization on RGB can be useful to enhance specific colour channels to achieve the desirable results. However, an image's colour balance can become distorted, causing an unnatural-looking image. Subsequently, histogram equalization on YUV provides a better advantage than RGB since it can take into account an image's brightness as well as colour. Therefore, careful considerations must be taken in order to choose which tool is best for enhancing a certain image to create the most desirable outcome.

4. Contrast Limited Adaptive Histogram Equalization (CLAHE) (Task 3)

After understanding the pros and cons of applying HE in the basic histogram, improvements have been explored to implement in basic HE to fill up the lacks.

The formation of Contrast Limited Adaptive Histogram Equalization (CLAHE) is a combination of the Contrast Limited Histogram Equalization (CLHE) and Adaptive Histogram Equalization (AHE).

a. <u>Contrast Limited Histogram Equalization (CLHE)</u>

The main key concept of contrast-limited histogram equalization (CLHE) is to fill up the density threshold, which dips below the clip limit and uses the user-set clip limit to fill up the density. By performing this, it allows the total intensity of the image to be maintained.
Based on the HE algorithm implemented by the team in task 2, in order to make the entire image uniform, flattening of intensity is required to be done to the image as a whole. However, there are some concerns on the limitations described in the previous section on the current HE implementation, which are increasing noise and the occurrence of loss of details, which require to be overcome.
For explanation purposes, our team will use grayscale images as an example. The transformation function 'T' is affected by the image pixel distribution. The excessive probability density can result in the original pixel's grayscale value becoming too high after transformation, leading to extreme contrast enhancement. Therefore, CLHE is being introduced to overcome it.

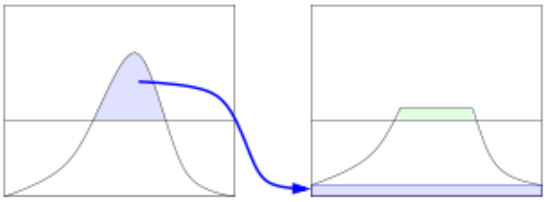


Figure 15: CLHE Algorithm

b. Adaptive Histogram Equalization (AHE)

AHE stands for Adaptive Histogram Equalization. It works on smaller tiles of the image. To implement this, first and foremost, we separate the image into smaller tiles and apply HE to each tile. The pixel value distribution for each tile is discontinuous, which causes strong segmentation that looks like a grid.

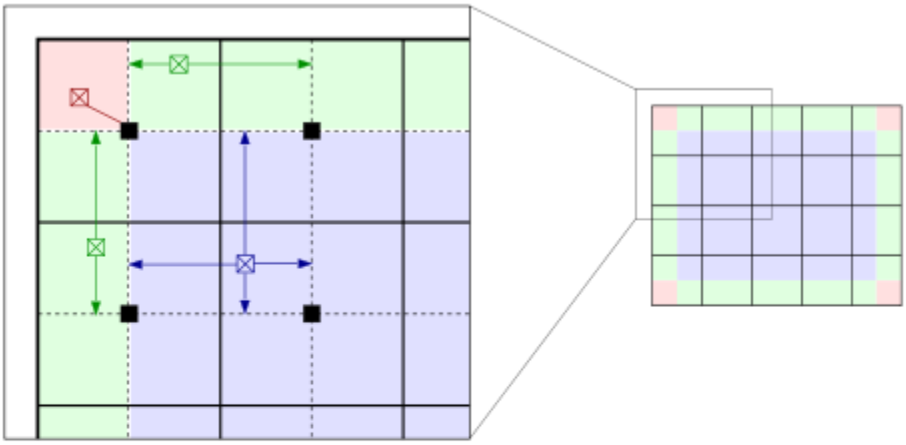


Figure 16. Bilinear Interpolation-based AHE is being raised (HE in the partition)

To resolve the problem above, Bilinear Interpolation-based AHE is being raised (Refer to Figure 13). Pixels in blue are bilinearly interpolated after applying the four adjacent subgraph transformation functions. Pixels near the boundary that are in the green area are linearly interpolated. Pixels in the red area are transformed by using the transform function.

c. Contrast Limited Adaptive Histogram Equalization (CLAHE)

As described, the Contrast Limited Adaptive Histogram Equalization is the combination of CLHE and AHE, and our team has implemented our own custom CLAHE, where we have merged using both colour space models: YUV and RGB.

Different combinations of the clip limits and title grid sizes have been experimented with to search for the optimal result to achieve a good-quality image, as the clip limits and title grid size will affect thequality of the output images. The best combination based on our experiment is Clip Limit =8 and titleGridsize = 2,2.

Figure 17. Image generated from the Custom CLAHE (top: sample 1, bottom: sample 6)

Based on the evaluation and comparison, we can conclude that our Custom CLAHE can generate an improved quality image compared to YUV or RGB. For example, from the sample 1 image, we can see the clear tile line at the wall and the Chinese character clearly (circled in red), while in sample 6, no information is lost since we can still see the background from the windows. In addition, sample 6 is more balanced and visible than the original images.

5. Conclusion

In conclusion, by experimenting with different approaches, our teams have highlighted the pros and cons of applying histogram equalization to the sample images. Our observation is that not all images are suitable for HE adoption due to the main concern in increasing noise, potential loss of information and change of image colour, which is different from the original. Therefore, improvements like CLAHE are being implemented to allow better control over the image enhancement where the HE lacks. Appropriate image enhancement techniques or algorithms are to be introduced to address the diversity of images, allowing for better image quality and visibility.

References

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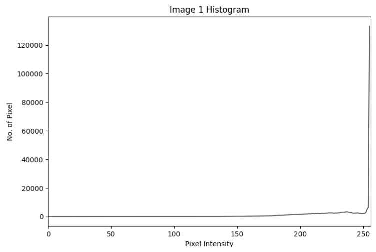
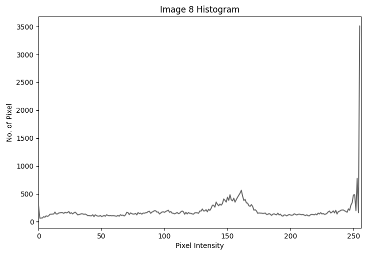
Appendix

1. All Sample images generated for the Data Understanding Histogram

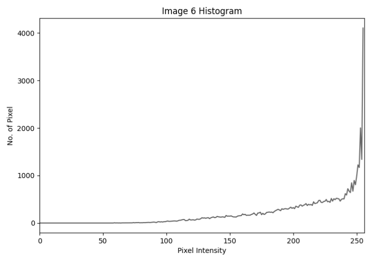
Sample 1:



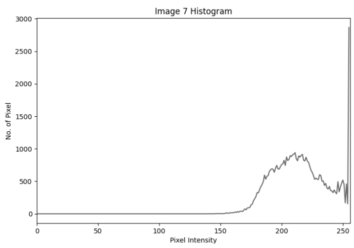
Sample 2:



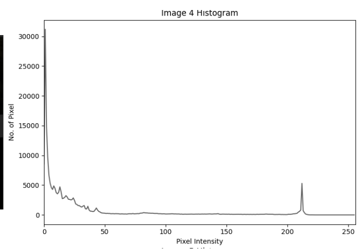
Sample 3:



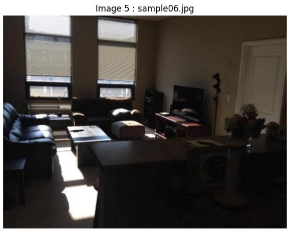
Sample 4:

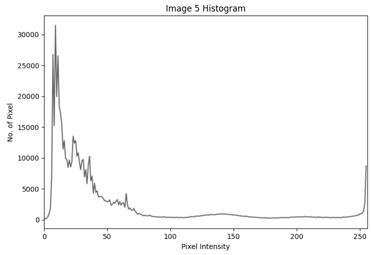


Sample 5:

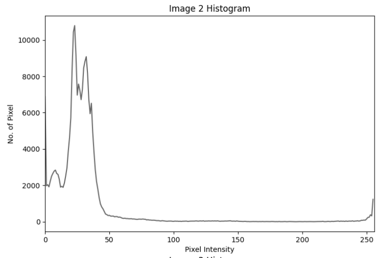


Sample 6:

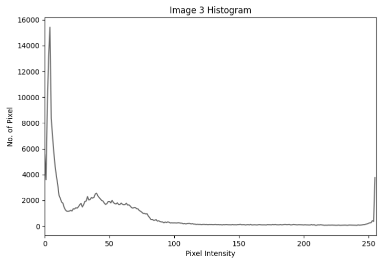




Sample 7:



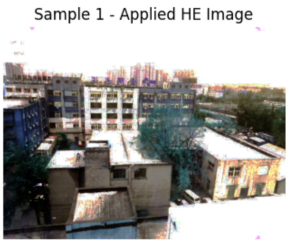
Sample 8:

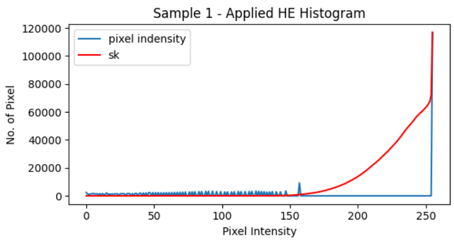


2. All Histogram Equalization for all 8 sample images

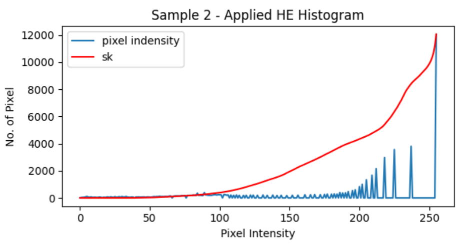
<u>Basic HE</u>

Sample1:

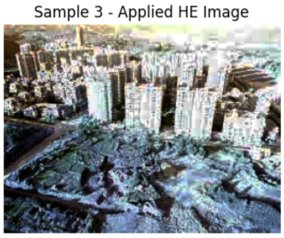


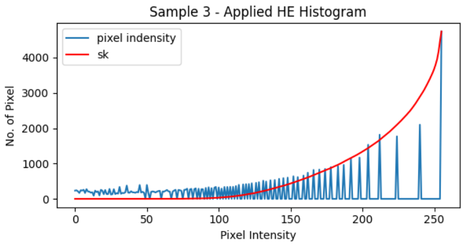


Sample2:

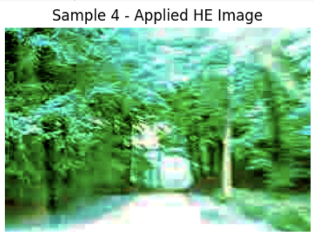


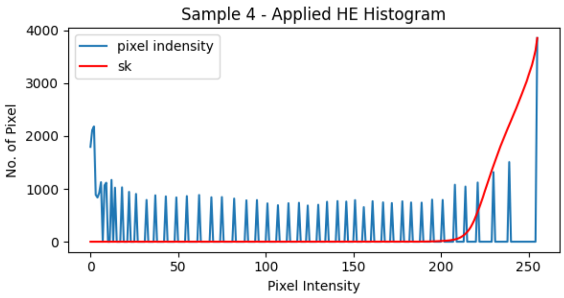
Sample3:



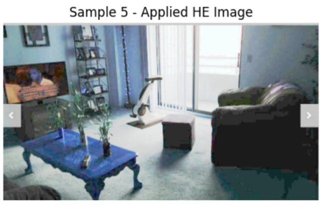


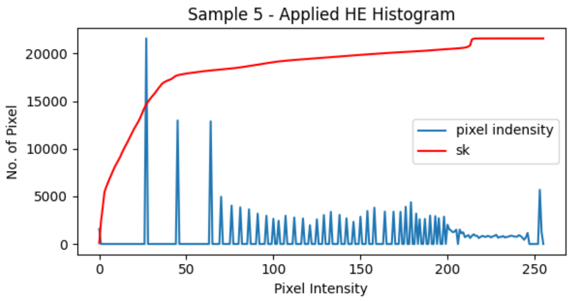
Sample4:



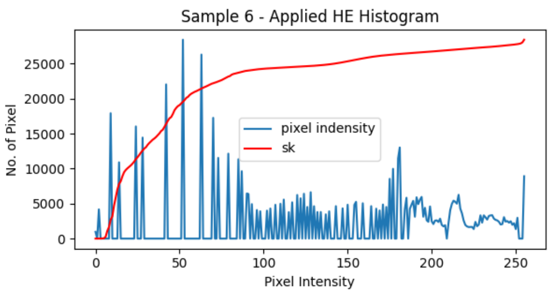


Sample5:

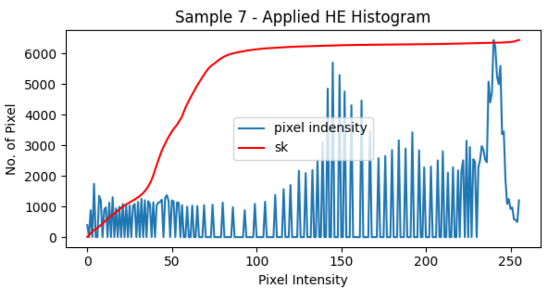




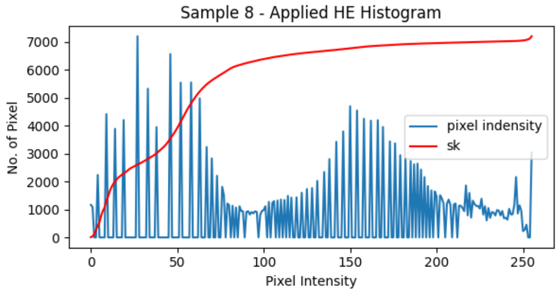
Sample6:



Sample7:

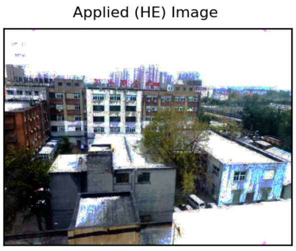


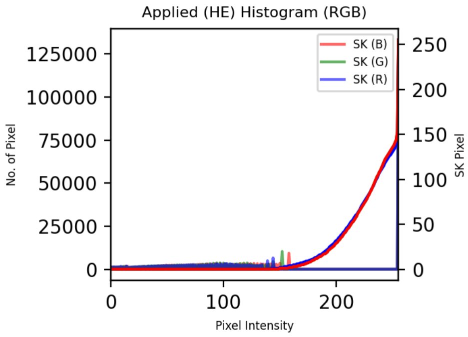
Sample8:



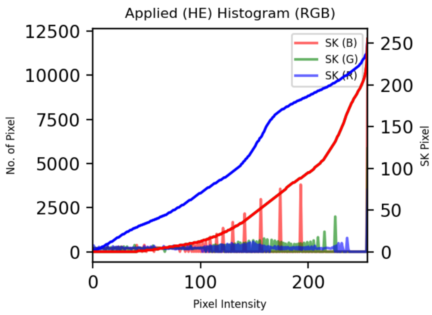
<u>RGB</u>

Sample1:

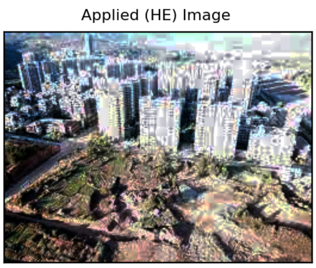


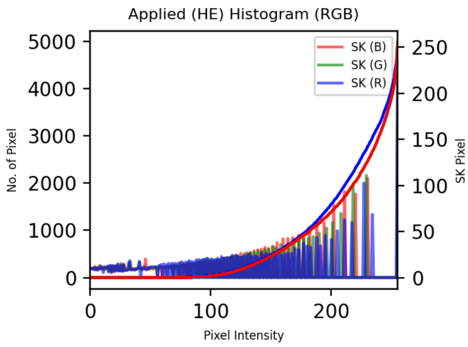


Sample2:

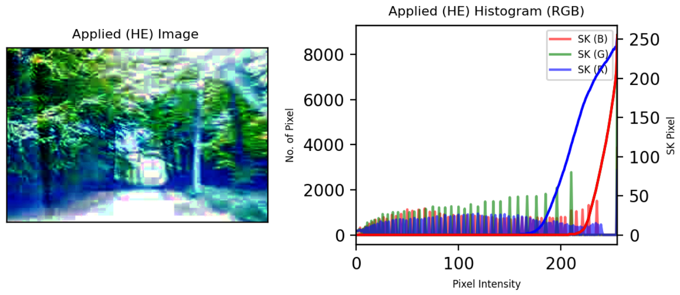


Sample 3:

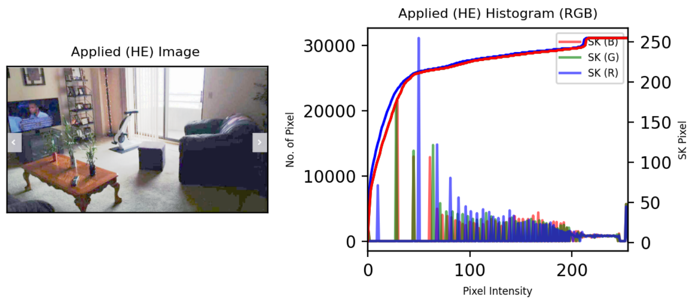




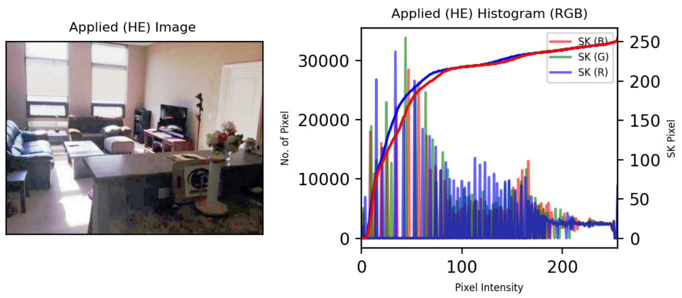
Sample 4:



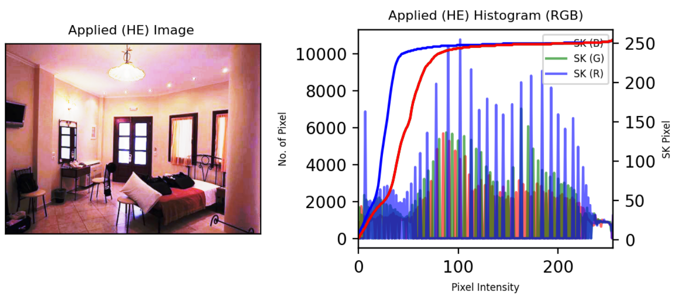
Sample 5:



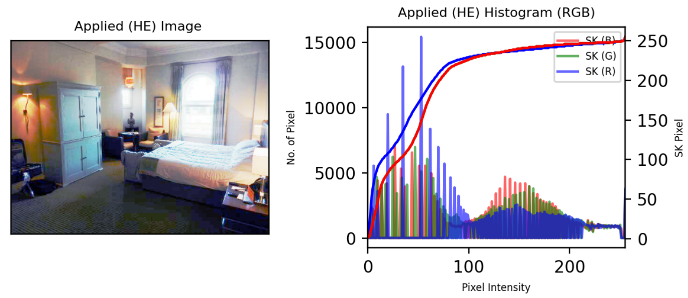
Sample 6:



Sample 7:

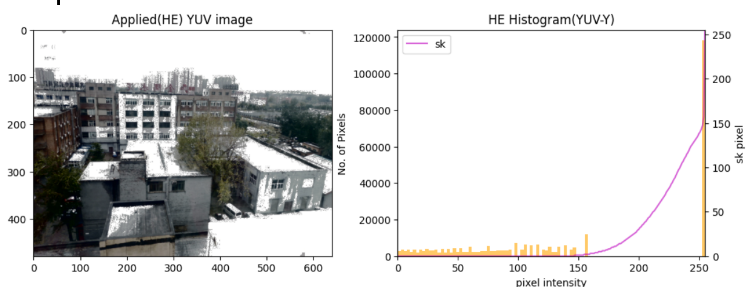


Sample 8:

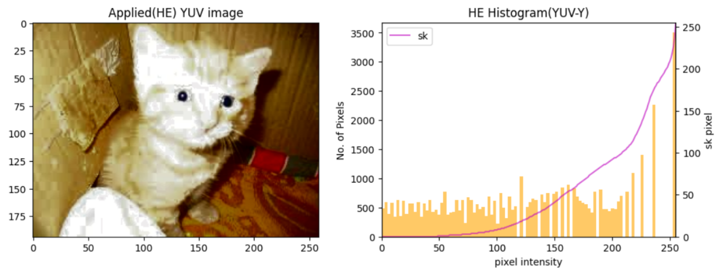


YUV

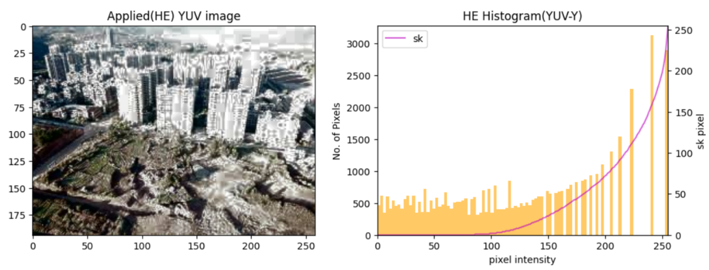
Sample 1:



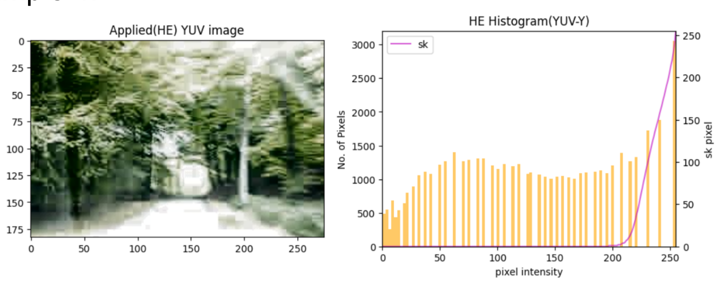
Sample 2:



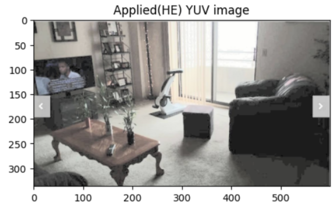
Sample 3:

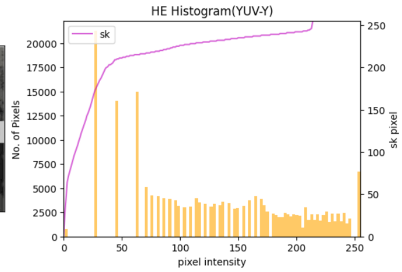


Sample 4:

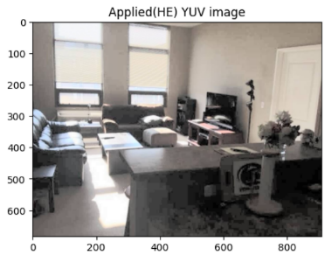


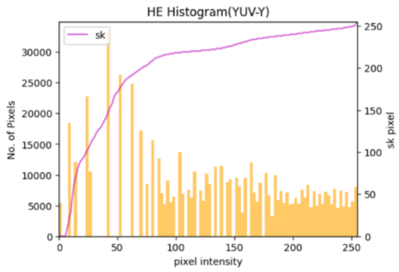
Sample 5:



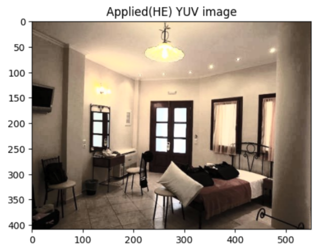


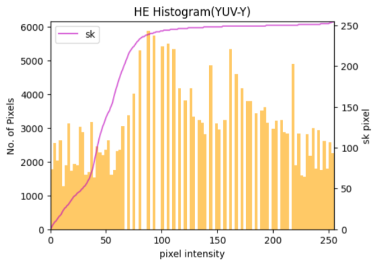
Sample 6:



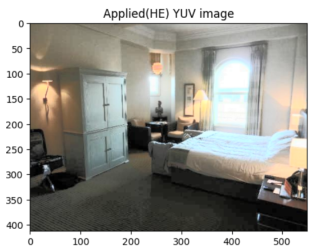


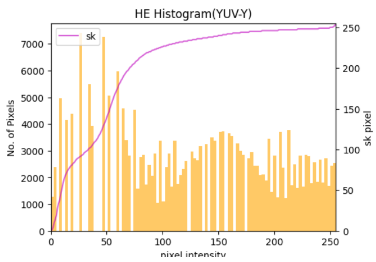
Sample 7:





Sample 8





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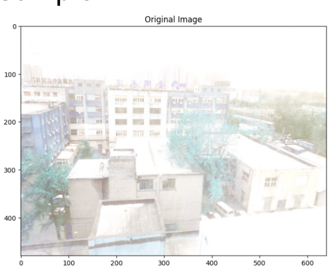
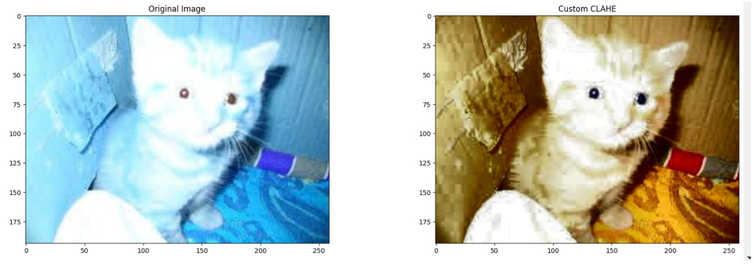
3. CLAHE images:

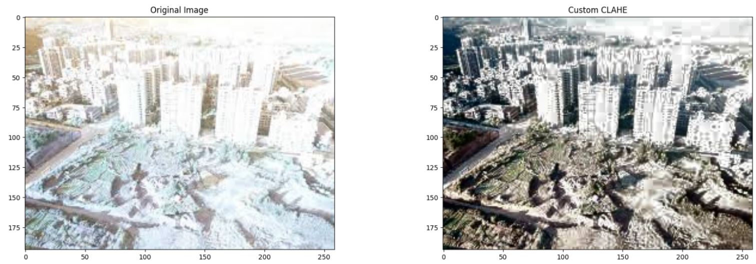
Sample 1:



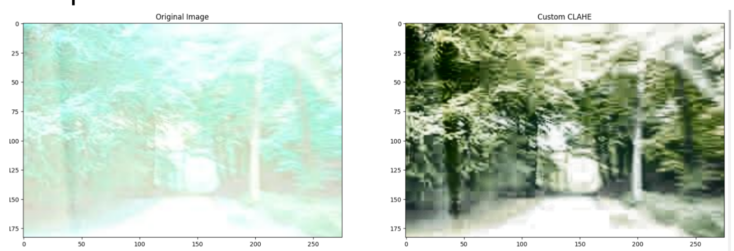
Sample 2:



Sample 3:



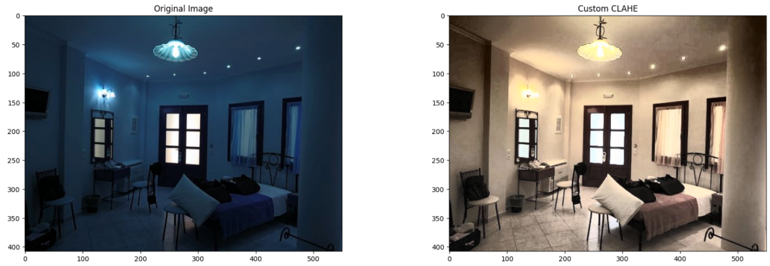
Sample 4:



Sample 5:

Sample 6:

Sample 7:



Sample 8: