Dhirubhai Ambani Institute of Information and Communication Technology

# MC315
# Independent Project - 1

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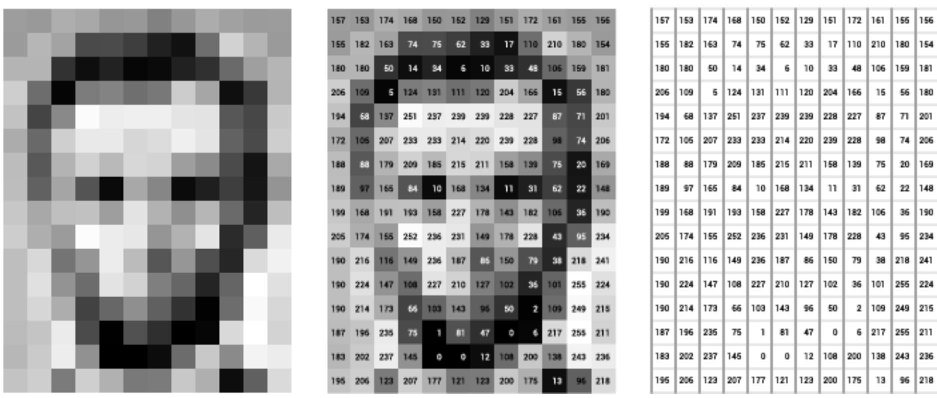
# Image Enhancement

**Abstract**

Image formulation is the base of image processing. A digital image is not every time as we want. To increase visual quality, reveal hidden details, work with some specific features and for improved human interpretation we use the most popular technique in image processing called Image enhancement. We can enhance image in multiple ways, we mostly work with histogram equalization, and histogram matching but also give some glimpse of intensity slicing, and contrast stretching. In the end, we work with colour space and show how to deal with colour images using the Reinhard method and the Modified Reinhard method for colour normalization.

## I. What is an image ?

Image is nothing but a 2-dimensional function. To represent the image we use the function f(x,y) where x and y are the spatial coordinates and the f(x,y) denotes the intensity value of a pixel.




The above image is a mathematical look of an image. An image is made with thousands of pixels and each pixel is filled up with some intensity value. The intensity value of a pixel depends on an easy function $2^k$ where k = no of bits. In image processing, a "bit" is the smallest unit of digital data, representing either a 0 or 1. It's crucial in determining image quality and colour depth. With more bits per pixel, images can represent a wider range of colours or shades of grey, leading to higher-quality visuals. In image processing, the intensity of a pixel is often represented using a formula like Intensity $= 2^k$, where $k$ denotes the number of bits allocated for that pixel. This equation illustrates that the intensity range increases exponentially with the number of bits. For instance, in an 8-bit image ($k = 8$), the intensity range spans from 0 to 255 (as $2^8 = 256$ possible intensity levels). Higher values of $k$ result in finer gradations of intensity, allowing for a more detailed and accurate representation of the image.

## II. Image Enhancement

**Why do we need Image enhancement ?**

Image enhancement is necessary because images captured in real-world scenarios often don't meet the desired quality standards or fail to convey the intended information effectively. Factors such as variations in lighting conditions, sensor limitations, and environmental interference can degrade image quality, obscuring important details or making interpretation difficult. By employing image enhancement techniques, we can adjust brightness, contrast, and sharpness to improve clarity, reveal hidden features, and ensure images accurately represent the intended information. This is crucial across various fields, including medical diagnostics, surveillance, remote sensing, and photography, where precise visualization is essential for decision-making and analysis.

**How can we do image enhancement ?**

**A.** Intensity Slicing
**B.** Contrast stretching
**C.** Histogram Equalization
**D.** Histogram Matching
**E.** Smoothing

The relationship between the intensity of the output image ($s$), the intensity of the input image ($r$), and the transformation function ($T$) can be expressed as:

$$s = T(r)$$

where:

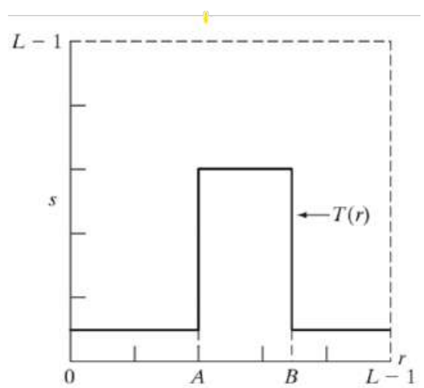
- $s$ is the intensity of the output image,
- $r$ is the intensity of the input image, and
- $T$ is the transformation function.

### A. *Intensity Slicing*

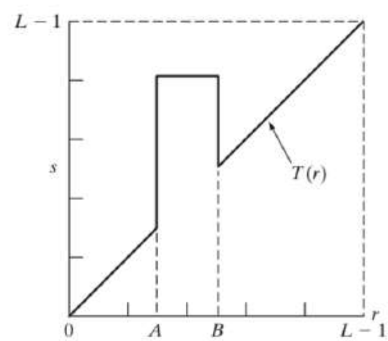
Intensity level slicing is a simple yet effective image enhancement technique used to highlight specific intensity ranges within an image.

Explanation:

- Selection of Intensity Range: In intensity level slicing, a particular range of intensity levels is selected based on the application requirements. For example, if we want to highlight objects with intensity values in a certain range, we choose that range accordingly.
- Thresholding: Once the intensity range is determined, thresholding is applied to segment the image. Pixels with intensity values falling within the selected range are retained, while pixels outside this range are usually set to a constant value such as black or white.




(a) $s = \begin{cases} l-1 & \text{if } A \leq r \leq B \\ 0 & \text{otherwise} \end{cases}$




(b) $s = \begin{cases} l-1 & \text{if } A \leq r \leq B \\ r & \text{otherwise} \end{cases}$

So, Intensity level slicing is commonly employed in various applications such as medical imaging (highlighting tissues with certain densities), object detection (emphasizing objects based on their brightness), and satellite imagery analysis (highlighting specific land cover types). It's a straightforward yet effective method for enhancing image visualization and aiding in subsequent analysis tasks.

### B. *Contrast Straching*

Contrast stretching is also an image enhancement technique that attempts to improve the contrast in an image by 'stretching' the range of intensity values it contains to span a desired range of values.

- Enhanced Contrast: By stretching the intensity values, the differences in brightness within the image are amplified, resulting in enhanced contrast. Dark areas become darker, light areas become lighter, and the overall visual clarity and definition of features are improved.

In contrast stretching, two pairs of values, $(r_1, r_2)$ and $(s_1, s_2)$, are chosen to define the input and output intensity ranges, respectively. These pairs represent the minimum and maximum original intensity values in the image ($r_1$ and $r_2$), and the desired minimum and maximum intensity values after contrast stretching ($s_1$ and $s_2$). Through a linear transformation, each original intensity value $r$ is mapped to a new intensity value $s$, expanding the dynamic range of the image. This mapping process enhances the visual contrast by making darker areas darker and lighter areas lighter, ultimately improving the overall quality and interpretability of the image.

### C. *Histogram Equilization*

Now our prime focus is on working with Histograms.

This equation set describes the process of histogram equalization, a technique used in image processing to enhance an image.

$$s_k = T(r_k)$$
$$s_k = (L-1)\sum_{j=0}^{k} p_r(r_j)$$
$$s_k = \frac{(L-1)}{MN}\sum_{j=0}^{k} n_j \quad \text{where } k = 0, 1, 2, \ldots, L-1.$$

Here we use the transformation function $\frac{(L-1)}{MN}\sum_{j=0}^{k} n_j$. is a uniform distribution. In image equalization what we try to do is to make intensity level equally distributed.

1. The first equation, $s_k = T(r_k)$, represents the mapping function $T$ that transforms the input pixel intensity $r_k$ to the corresponding output intensity $s_k$. This mapping function is responsible for adjusting the intensity levels in the image.

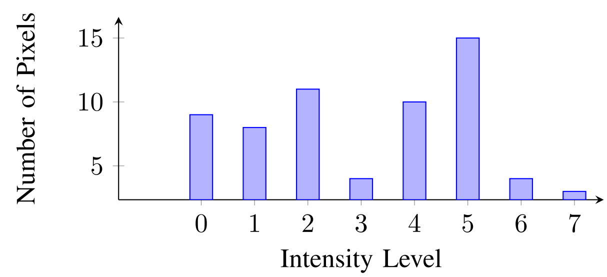
2. The second equation, $s_k = (L-1)\sum_{j=0}^{k} p_r(r_j)$, calculates the cumulative distribution function (CDF) of the input image histogram. Here, $p_r(r_j)$ represents the probability of occurrence of pixel intensity $r_j$. By multiplying the CDF by $(L-1)$, where $L$ is the number of intensity levels, we scale the CDF to the desired output range.

3. The third equation, $s_k = \frac{(L-1)}{MN}\sum_{j=0}^{k} n_j$, computes the histogram equalization transformation. Here, $n_j$ represents the histogram of the input image. By dividing the scaled cumulative histogram by the total number of pixels $MN$, we normalize the histogram to achieve an equal distribution of intensity levels.

In image equalization, the objective is to enhance the image's contrast and overall appearance by redistributing pixel intensities uniformly across the entire range of intensity values. This process helps to improve the image's visual quality and make it more visually appealing.

k=3-bit image with 8x8 size.
In the X-axis we take an intensity level and at Y-axis we take a number of pixels.

| Intensity level | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| No. of pixels | 9 | 8 | 11 | 4 | 10 | 15 | 4 | 3 |

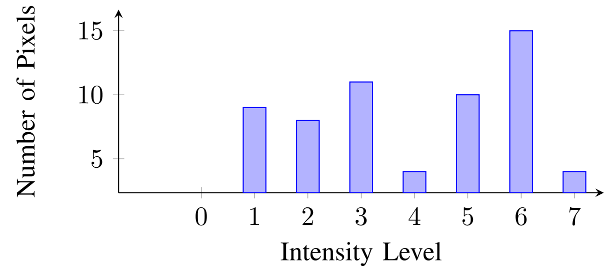



Here just for a demonstration we take a 3-bit image with an 8x8 size image.

| Intensity | Pixel | $P(r_k)$=$\frac{n_k}{k}$ | $\sum_{j=0}^{k} p(r_k)$ | $(L-1)\times\sum_{j=0}^{k} p(r_k)$ | Equalization level (s$_k$) |
|---|---|---|---|---|---|
| 0 | 9 | $\frac{9}{64} = 0.141$ | 0.141 | 0.987 | 1 |
| 1 | 8 | $\frac{8}{64} = 0.125$ | 0.266 | 1.862 | 2 |
| 2 | 11 | $\frac{11}{64} = 0.172$ | 0.438 | 3.066 | 3 |
| 3 | 4 | $\frac{4}{64} = 0.062$ | 0.5005 | 3.5035 | 4 |
| 4 | 10 | $\frac{10}{64} = 0.156$ | 0.6565 | 4.5955 | 5 |
| 5 | 15 | $\frac{15}{64} = 0.234$ | 0.8905 | 6.2335 | 6 |
| 6 | 4 | $\frac{4}{64} = 0.062$ | 0.953 | 6.671 | 7 |
| 7 | 3 | $\frac{3}{64} = 0.047$ | 1 | 7 | 7 |
| | Total = 64 | | | | |

After completing the calculation we got our new intensity level for pixels.

| Intensity level | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| No. of pixels | 9 | 8 | 11 | 4 | 10 | 15 | 7 |




### D. ***Histogram Matching***

In histogram matching, we're working with two pictures: one we want to improve (the source image) and another we want to use as a guide (the reference image). Instead of just adjusting intensity distribution like in normal histogram equalization, we're matching the source image's intensity distribution to the reference image's intensity distribution. We do this by looking at how the pixels are distributed in both images. First, we figure out how intensity is distributed in each image overall. Then, we adjust the source image to match the reference image. This helps us make the source image look more like the reference image, which can be handy for things like making photos taken in different lighting conditions look consistent.

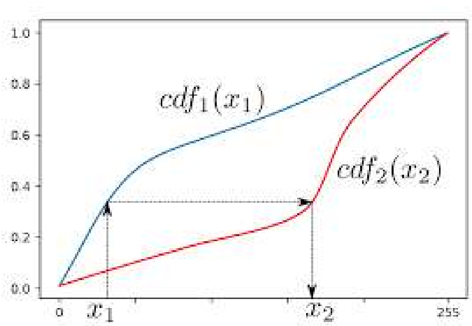
The methodology is almost similar to histogram equalization. firstly we have to calculate an equilize histogram for both images then after we map with the function g(z) = s.

$$s_k = T(r_k)$$
$$s_k = (L-1)\sum_{j=0}^{k} p_r(r_j)$$
$$s_k = \frac{(L-1)}{MN}\sum_{j=0}^{k} n_j \quad \text{where } k = 0, 1, 2, \ldots, L-1.$$

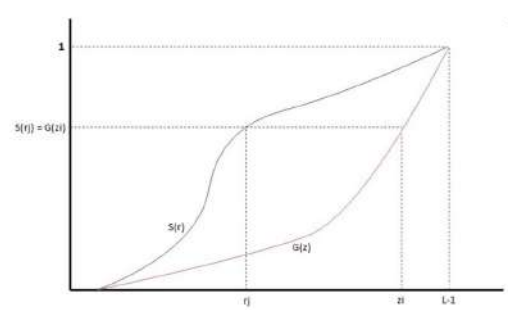
After calculating $s_k$ for the source image and $z_q$ for the source image we have to map with the map function.

$$G(z_q) = s_k$$

Now understand how for uniform distribute we work of cdf(commutative distribution function) to distribute intensity in pixels.




(a)



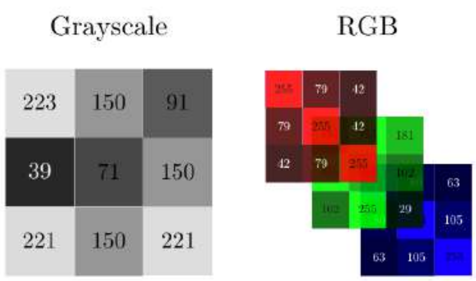

(b)

- Histogram Calculation: Initially, the histogram of the input image is calculated, which provides information about the distribution of pixel intensities across the image.

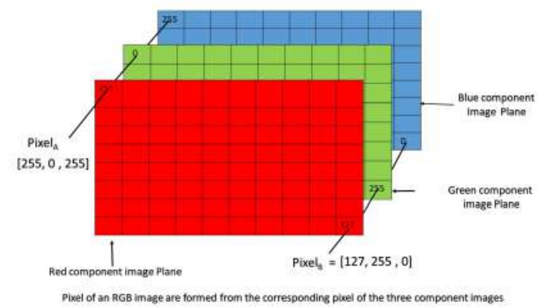
- Cumulative Distribution Function (CDF): Next, a cumulative distribution function is computed from the histogram. The CDF represents the cumulative sum of histogram values and provides a mapping from the original intensity values to new intensity values.
- Histogram Equalization: In histogram equalization, the goal is to redistribute the pixel intensity values in such a way that the histogram becomes more uniformly distributed across the entire intensity range. This is achieved by stretching the CDF such that it covers the full range of intensity values.
- Transformation Function: A transformation function is generated based on the modified CDF. This function maps each pixel's original intensity value to a new intensity value, effectively enhancing the contrast of the image.

## III. Color Channels

Colour channels are fundamental components in digital images, representing specific colour information that contributes to the overall appearance of an image. In RGB (Red, Green, Blue) colour space, which is the most common representation in digital imaging, each pixel is composed of three separate channels: red, green, and blue.




(a)




(b)

RGB is known as the primary colour model in digital images. By mixing different amounts of red, green, and blue, we can create millions of colours. However, unlike paints where you can separate red, green, and blue, in RGB, these colours are closely connected. For example, if you want to reduce the redness in a picture and lower the intensity of the red channel, it affects the overall colour because red, green, and blue are intertwined. Lowering the red intensity might make the picture look greener or bluer because these colours are all linked together. This close relationship between red, green, and blue is why we say they are highly correlated.

Similar to RGB there are more colour channels like HSI, CMYK, HSV, XYZ, YUV, LAB etc.....

**LAB colour model :** The LAB colour model is a way to describe colours that's different from the more common RGB model. Instead of using red, green, and blue as primary colours, LAB uses three different components: L, A, and B.

- L: Stands for Lightness. It measures how bright or dark a colour is. Higher L values mean brighter colours, while lower values mean darker colours.
- A: Represents the colour along a green-to-red axis. Positive A values indicate more red, while negative values indicate more green.
- B: Represents the colour along a blue-to-yellow axis. Positive B values indicate more yellow, while negative values indicate more blue.

In the LAB colour space, the components (L for luminance, A for green-red, and B for blue-yellow) are uncorrelated, which means that changes made to one component do not directly impact the others. This independence allows for more precise and targeted adjustments during colour manipulation tasks, as alterations in luminance, for instance, won't inadvertently affect the green-red or blue-yellow channels. As a result, LAB proves to be an invaluable tool in colour correction and normalization processes, offering granular control over individual colour components and facilitating nuanced adjustments for achieving desired visual outcomes.

The property of the above uncorelation helped us to normalise colour. In our application part, we use Lab colour space. The Renihard problem and modified reinhard problem are typically working with the LAB colour space.

## IV. Reinhard Problem

The Reinhard method, introduced by Erik Reinhard in 2001, revolutionized colour transfer between images by leveraging their global statistics, notably mean and standard deviation. This technique enables the seamless transference of colour characteristics from one image to another, fostering a nuanced exchange of visual aesthetics. By analyzing the statistical distribution of colours within an image, Reinhard's approach discerns key attributes such as overall colour tone and contrast, encapsulating the essence of its visual identity.

Reinhard is similar to histogram matching here we work with two images source and reference image. While Reinhard method focuses on global statistics like mean and standard deviation to transfer overall colour characteristics, histogram matching aligns the frequency of colours between images by adjusting their histograms. Despite their different approaches, both methods globally analyze images and apply non-localized changes, making them valuable tools for tasks such as colour grading, style transfer, and image enhancement in various fields of image processing and computer vision.

Reinhard method works effectively on almost every image, primarily working with the LAB colour space rather than the RGB colour space due to its uncorrelated relationship with its colour channels. Reinhard focuses solely on the chrominance ('a' and 'b') colour channels, disregarding the luminance channel. The method's objective is to normalize colours and impose the colour characteristics of a reference image onto a source image

$$
\begin{aligned}
a_n &= \mu_{\text{global}}(a_r) + \left( [a_s - \mu_{\text{global}}(a_s)] \times \frac{\sigma_{\text{global}}(a_r)}{\sigma_{\text{global}}(a_s)} \right) \\
b_n &= \mu_{\text{global}}(b_r) + \left( [b_s - \mu_{\text{global}}(b_s)] \times \frac{\sigma_{\text{global}}(b_r)}{\sigma_{\text{global}}(b_s)} \right)
\end{aligned}
$$

where:

$$
\begin{aligned}
\mu_{\text{global}}(a_r) &= \text{Mean of the reference image in channel } a, \\
\mu_{\text{global}}(a_s) &= \text{Mean of the source image in channel } a, \\
\sigma_{\text{global}}(a_r) &= \text{Variance of the reference image in channel } a, \\
\sigma_{\text{global}}(a_s) &= \text{Variance of the source image in channel } a, \\
\mu_{\text{global}}(b_r) &= \text{Mean of the reference image in channel } b, \\
\mu_{\text{global}}(b_s) &= \text{Mean of the source image in channel } b, \\
\sigma_{\text{global}}(b_r) &= \text{Variance of the reference image in channel } b, \\
\sigma_{\text{global}}(b_s) &= \text{Variance of the source image in channel } b.
\end{aligned}
$$

The Reinhard method adjusts the colours of a source image to match the mean and variance of a reference image using colour normalization. By applying statistical properties from the reference image, it ensures a consistent colour palette across images. From the equation given above, we clearly see the working of a Reinhard method. So Reinhard method is a global colour normalization method. Reinhard method demonstrates that a colour space with decorrelated axes is a useful tool for manipulating colour images. Imposing mean and standard deviation onto the data points is a simple operation, which produces believable output images given suitable input images.


(a) Source (b) Reference (c) Output

Fig. 4: Reinhard method for global image colour normalization

When we implement the code for the Reinhard method, we observe a notable alteration in the colour of the resultant image. Although Reinhard typically proves effective across a wide range of images, there arises a need for more tailored outputs but sometimes we want more specific results. That's where the "Modified Reinhard Method" comes in. It's a new or changed way of doing things that's become popular.

## V. Modified Reinhard Problem

Reinhard method is effective in many scenarios, but it may not always produce satisfactory results under certain conditions or for particular types of images. Modified is the special case or particularly developed method for histopathology H&E images. Where H = Hematoxylin stain and E = Eosin stain. This has been observed that the Hematoxylin stain is closely bounded to the nuclei (blue colour) and the Eosin stain is limited to only the cytoplasm (Redish purple colour). Therefore, many researchers have employed stain separation methods to separate Hematoxylin-only channels and Eosin-only channels. We have observed that this stain separation is only required if there is a colour artefact present in the image and they are affecting the important parts like nuclei, lymphocytes, stroma etc in H&E stained histopathology images.

In 2021 Santanu Roy, Shubhajit Panda and Mahesh Jangid introduced a modified Reinhard method for colour Normalization of colourectal Cancer Histopathology Images. Modified Reinhard method is working on LAB colour space similar to Reinhard but here Modified is also working with Luminance channel.

$$q = \frac{\sigma_{\text{global}}(l_r) - \sigma_{\text{global}}(l_s)}{\sigma_{\text{global}}(l_r)}$$

$$\sigma_{\text{global}}(l_r) = \text{Variance of reference image for luminance channel.}$$
$$\sigma_{\text{global}}(l_s) = \text{Variance of source image for luminance channel.}$$

Here q denotes the contrast difference between source and reference image. Here they propose two possible cases.

if $q > 0$ then

$$l_n = \mu_{\text{global}}(l_s) + [l_s - \mu_{\text{global}}(l_s)] \cdot (1 + q)$$

otherwise $q \leq 0$ then

$$l_n = \mu_{\text{global}}(l_s) + [l_s - \mu_{\text{global}}(l_s)] \cdot (1 + 0.05)$$

So in essence, the 'q' parameter allows adapting the luminance contrast enhancement based on the reference image's contrast relative to the source image. This satisfies the hypothesis that the normalized image's contrast should be greater than or equal to the source image's contrast.

Working with a and b channels is the same as Reinhard method.

$$a_n = \mu_{\text{global}}(a_r) + \left( [a_s - \mu_{\text{global}}(a_s)] \times \frac{\sigma_{\text{global}}(a_r)}{\sigma_{\text{global}}(a_s)} \right)$$
$$b_n = \mu_{\text{global}}(b_r) + \left( [b_s - \mu_{\text{global}}(b_s)] \times \frac{\sigma_{\text{global}}(b_r)}{\sigma_{\text{global}}(b_s)} \right)$$

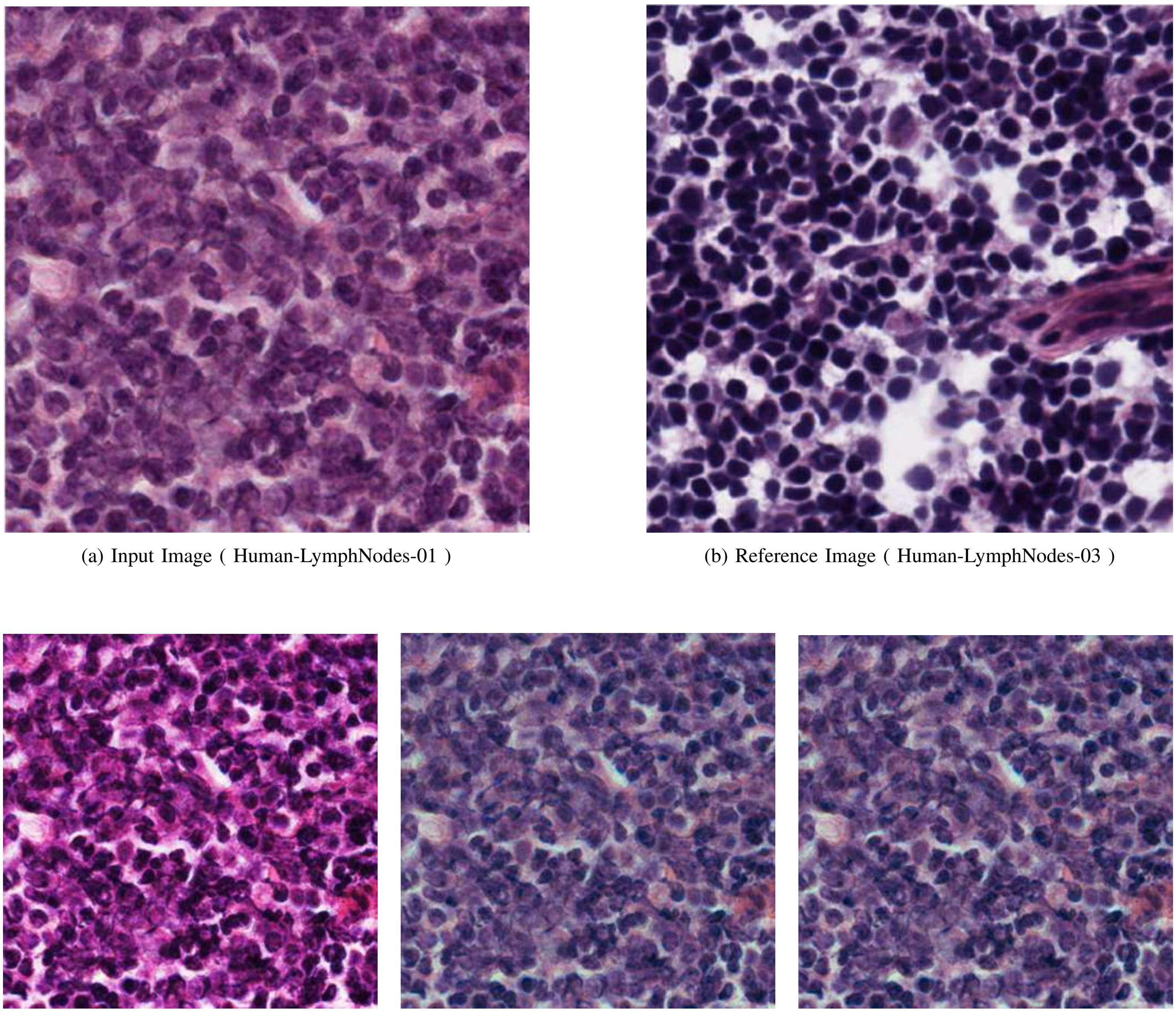
Here the process for the other two channels are same. Due to its change in luminance channel, we restricted to use of this method for specific images. The reason and also I observe is that if $q > 0$ then it changes the whole luminance channel sometimes its intensity becomes 240+ which shows nothing but white space. Here we discuss the basic intuition and from the aspect of maths but the main work is on the implement side where you implement the method and observe the specific result. Further, we show the implementation of different methods.

## VI. Implementation

Now Implement the enhancement method that we describe and see the results of the enhanced image. To get implemented I work with Google Collab where I write code for each method to show and compare the results. I share the drive link at the end of the report. Below I demonstrate the result of the method that we learned above with input image (Source image) and Reference Image. We apply the following method of enhancement

Our basic aim is to highlight stains from the image by using methods.

- Histogram Matching
- Reinhard
- Modified Reinhard



(a) Input Image ( Human-LymphNodes-01 )

(b) Reference Image ( Human-LymphNodes-03 )

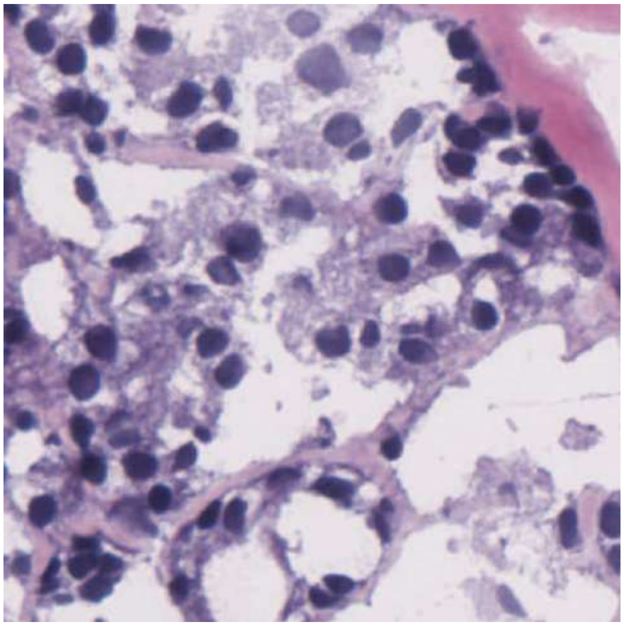
(c) Histogram Matching

(d) Reinhard

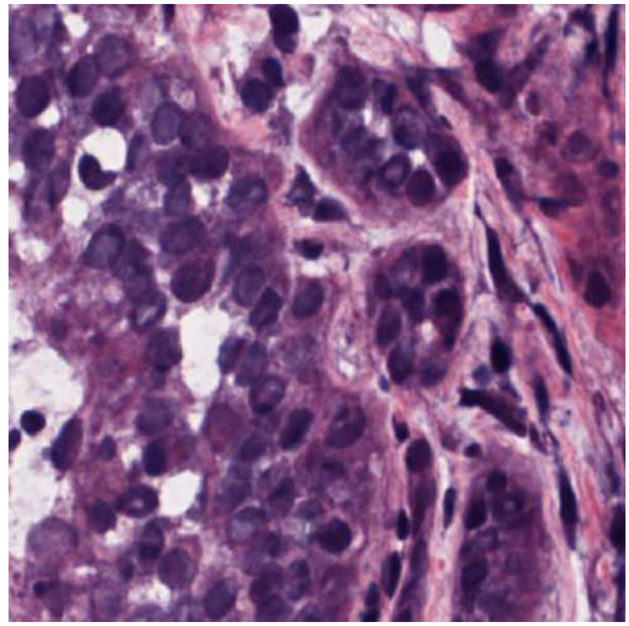
(e) Modified Reinhard

Fig. 5: Implementation - 1

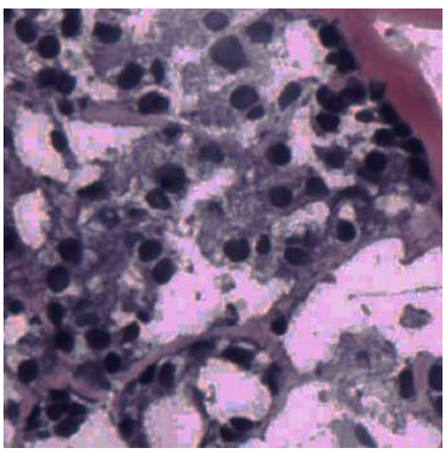
This image is for ThyroidGland. We see the result of applying those three methods: Histogram matching, the Reinhard method and the Modified Reinhard method.



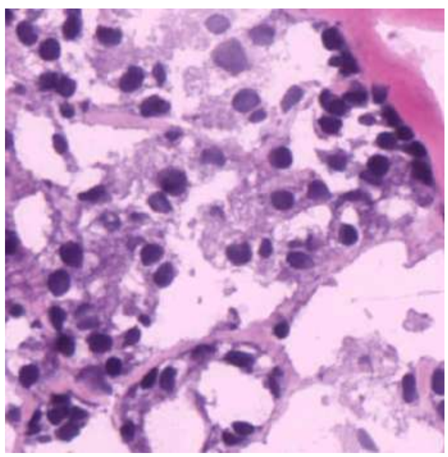
(a) Input Image ( Human-ThyroidGland-01 )



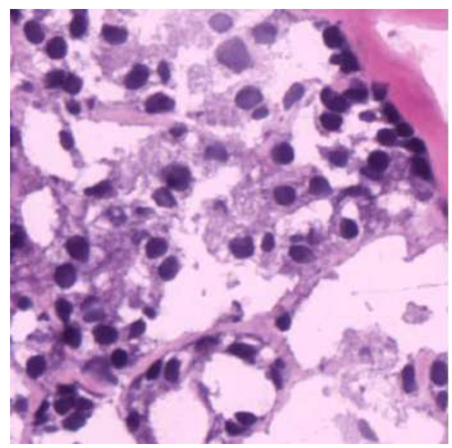
(b) Reference Image ( Human-ThyroidGland-03 )



(c) Histogram Matching



(d) Reinhard

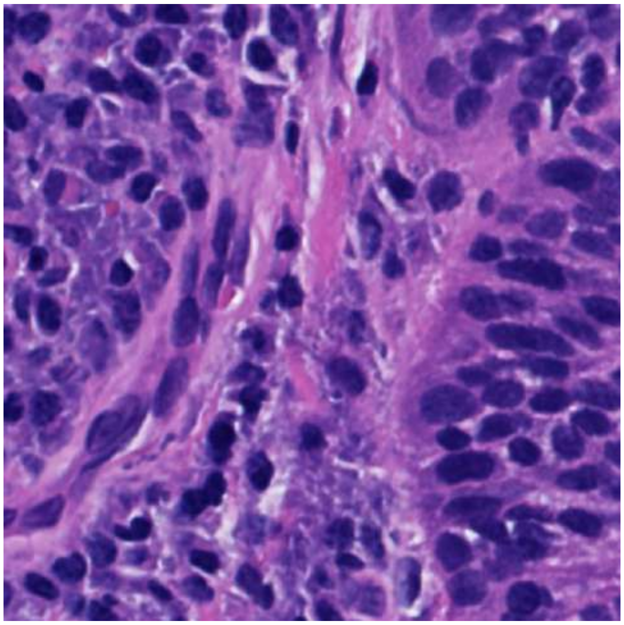


(e) Modified Reinhard

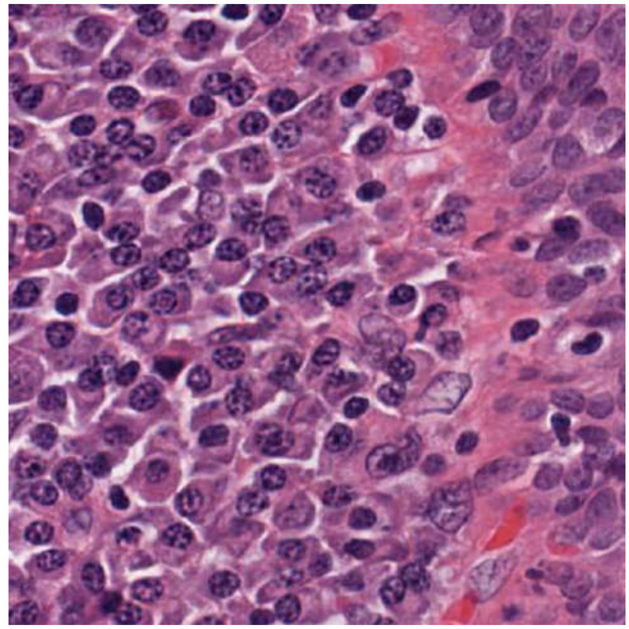
Fig. 6: Implementation - 2

Comparing different methods we analyse how histogram matching ruins the image and is not even close to identifying the stain. while Reinhard is global colour normalization method gives you appropriate results unless the modified method comes into the field. We can identify the stain easily in the modified Reinhard method.

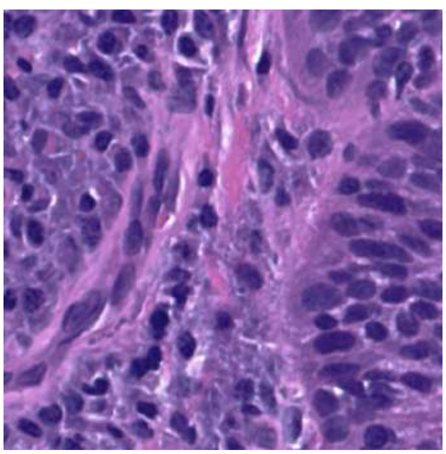
This image is for the Larynx (voice box) Located in the neck at the top of the trachea or windpipe. We see the result of applying those three methods: Histogram matching, the Reinhard method and the Modified Reinhard method.



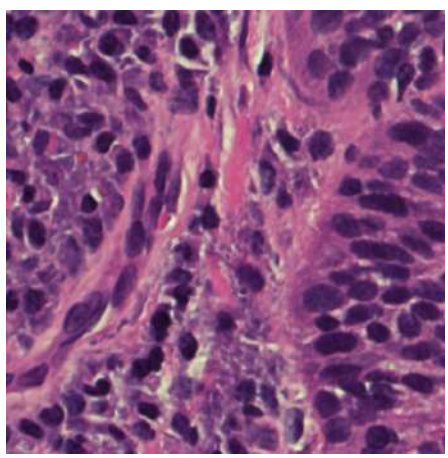
(a) Input Image ( Human-Larynx-01 )



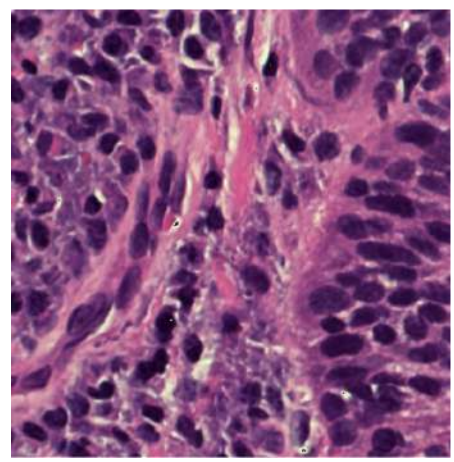
(b) Reference Image ( Human-Larynx-02 )



(c) Histogram Matching



(d) Reinhard



(e) Modified Reinhard

Fig. 7: Implementation - 3

## VII. Conclusion

In the digital world, working with images is common, but often, images may not be suitable for their intended purpose. Image enhancement techniques help create better visuals by adjusting colours, contrast, and other factors. In the medical field, images are crucial for diagnosing diseases, where specific areas need highlighting and precise visualization without alteration. The Reinhard method, a global colour correction technique, enhances images by adjusting colours to match a reference image, improving overall visual quality. Conversely, the modified Reinhard method is tailored for biological applications, ensuring an accurate representation of histopathological specimens. Despite their differences, both methods share a fundamental concept rooted in image processing: histogram matching, which adjusts the colour distribution to align with a reference histogram.

## VIII. Code of the implementation different methods

Learning Image processing by only intuition is not possible. I do code from scratch for methods and fundamental to the end of enhancement techniques. For learning image processing implementation is the major and crucial part.

Here I provide two links to my work

- Image processing from scratch : Link
- Code of every methods : Link

## References

[1] Digital Image Processing 3rd ed. - R. Gonzalez, R. Woods
[2] colour transfer between images by E. Reinhard 2001 (Reinhard)
[3] Modified Reinhard Algorithm for colour Normalization of colorectal Cancer Histopathology Images (Modified Reinhard)