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Identification of Suitable Contrast Enhancement Technique for Improving the Quality of Astrocytoma Histopathological Images.

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Abstract

Contrast enhancement plays an important part in image processing. In histology, the application of a contrast enhancement technique is necessary since it can help pathologists in diagnosing the sample slides by increasing the visibility of the morphological and features of cells in an image. Various image enhancement techniques have been proposed to enhance the contrast of microscopic images. Thus, this paper aims to study the effectiveness of contrast enhancement techniques in improving the quality of astrocytoma histopathological images. An automated image enhancement method was proposed by using three different contrast enhancement techniques. These techniques consist of contrast stretching, histogram equalization, and CLAHE techniques. Thirty histopathological images of astrocytoma are used to perform tests. The performance and the quality of each enhanced image produced from each technique were compared by computing ten quantitative measures. This study shows only contrast stretching and CLAHE techniques are suitable for the use of enhancing the quality of astrocytoma images.

Key Words: Astrocytoma**,** Automated Image Enhancement, CLAHE**,** Contrast Enhancement, Contrast Stretching, Histogram Equalization, Ki67.

1 Introduction

Astrocytoma is a type of glioma tumour. Glioma is referring to a group of tumours that originates from "glial" cells, which located inside the brain. Gliomas cover approximately 30% of all brain and central nervous system tumours, and also 80% of all malignant brain tumours [1]. The astrocytoma is a tumour that arises in the star-shaped cell (astrocytes) that acts as supportive tissues in the brain. The nuclear protein (Ki67) was the most common proliferation marker used to measure cell proliferation activity. Immunohistochemistry (IHC) staining is commonly used to identify the presence of specific protein markers that may facilitate the pathologists in identifying and diagnosing the abnormal cells such as cancerous tumours.

Nowadays, the study of digital pathology imaging is surely increasing since it can improve the quality of pathologists' works in examining and diagnosing a disease. With the aid of computer tools, the

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pathologists can visualize and analyse the images of pathologic cells and tissue samples in a high-resolution image.

The digital pathology images can be acquired by capturing the stained specimen on the glass slide through a digital camera or scanning device. However, some of the captured images have poor quality. The "poor quality" is referring to the lack of contrast, low colour intensity, existing noise in the image, weak edges, and inhomogeneity of intensity [2]. These drawbacks can affect the analysis and finally lead to low diagnostic accuracy results. To overcome these issues, it is required to enhance the quality of the captured images before further analysis. Image enhancement is one area of digital image processing. Image enhancement technique can improve the important aspects and visual appearance of an image. The objective of this technique is to process an image so that the result would be more acceptable than the original image for a specific application.

2 Previous Works

The objective of image enhancement includes removing noise, sharpening an image, brightening an image, enhancing the contrast of an image, and reduction and magnification of an image. These objectives and techniques may vary with the applications. Research studies have shown enormous applications of image enhancement techniques in many areas, including medical fields.

Kaur and Singh [3] proposed a contrast enhancement technique by using wavelet-based modified adaptive histogram equalization for enhancing cephalometric images. At the early stage, the proposed system will divide the image into several blocks that have an equal size. Then, a modified histogram is computed for each block of the image. This modified histogram consists of two major procedures. First, the biorthogonal spline wavelets were used to identify the edge pixels and discard the pixels in the homogeneous region while computing image histograms. Second, the contrast-limited adaptive histogram equalization (CLAHE) technique is applied to the modified histogram for reducing the histogram spikes. The computing process for each block was done to find the derived mapping function for each block. This derived mapping function will be used to enhance the centre pixels in each block. For the remaining pixels, a transformation function is calculated by interpolating the four neighbouring mapping functions. This function later will be utilized to the remaining pixels to get the output image. For measuring the performance of the proposed system, eight quantitative measures were analysed, which include contrast enhancement, brightness preservation, edge conservation and enhancement, preservation of image structures, and non-addition distortion analysis. Based on the results, the proposed system was able to enhance the cephalometric images with good contrast enhancement, better brightness preservation without losing edge information, and less addition of distortions to the enhanced images.

Muhimmah, Wijaya and Indrayanti [4] had investigated and implemented a nonlinear mapping technique to normalize the appearance of each stain and enhancing the contrast of histopathology images of breast cancer. Two input images were required in this study, which acts as the source and target images. The target image functioned as a reference image, while the source image was the image that needs to be corrected. The proposed method was divided into four modules. It consists of stain matrix estimation, colour deconvolution, nonlinear mapping of channel statistics, and reconstruction. At first, the stain deconvolution matrix was applied to the target and source images for converting the RGB colour space of those images into a new colour space defined by constituent stains. Then, the spline-based nonlinear mapping was applied to each channel of deconvolved target and source images for calculating the statistics set and their corresponding probability map. Finally, each stain channel was recombined and reconstructed on a per-pixel basis to obtain the normalized source image. Based on 59 datasets, the proposed method achieved a positive agreement with the expert criteria of 96.6%.

Pandey, Jain, and Khatri [5] presented a method of enhancement by using the Kalman filter for enhancing various medical images. The proposed framework consists of several processes, which are colour space conversion, noise addition, and filtering. In the beginning, the colour space of the sample image was converted into a grayscale colour space. Then, the system will add Gaussian noise to the processed image. Later, the Wiener filter was applied to remove the noise. The iterative two dimensional Kalman filter was being used for better enhancement. In this paper, the iteration Kalman filter was done for eight times to provide a good enhanced image. The Kalman filter was added after the digital to the analogue conversion process. Different types of medical images were tested in this study. This involves

computed tomography (CT) MR images, and ultrasound and X-ray images. Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE) of the proposed framework were calculated and compared with the Median Filter technique for analysing purpose. The experimental results showed the PSNR values obtained by the proposed system were higher than the values obtained by using the Kalman filter. The results also showed there was a drop of MSE values when the proposed system is applied.

Kumar, Asha, Manish and Muthulakshmi [6] had applied the image enhancement techniques for enhancing the pneumonia bacteria images. In this study, the authors used different image enhancement techniques on different types of images. For grayscale images, the authors used the median and Wiener filters for enhancing the quality of the sample images. Meanwhile, for colour images, the single scale and multiscale retinex were used for colour enhancement purposes. PSNR and MSE were computed to find the most suitable technique for each type of images. The authors concluded that the application of the median filter was better than the Wiener filter in enhancing the quality of grayscale images. This was due to higher PSNR results obtained by using the median filter compared to the Wiener filter. For colour images, the multiscale retinex was selected as the best method for colour enhancement.

Singh *et al.* [7] introduced an idea of removing blurring artefacts by applying the dark channel algorithm to the medical images. The proposed algorithm was divided into two sections, which are the dark channel algorithm and gamma correction. At first, the dark channel algorithm was applied to the input image for eliminating the blurring or vagueness that existed in the image. Second, by defining a specific value of gamma, the proposed system applied the gamma correction to increase the brightness and clarity of the image. Various medical images include the ultrasound image, magnetic resonance (MR) image, microscopic image, angiogram image, and retinal image were tested in this study. The Structural Similarity Index (SSIM) and Correlation Coefficient analysis were calculated for measuring the quality of the resultant images produced by the proposed system. The results were compared with other previous work. It is shown that the value of the correlation factor obtained by the proposed system was better than the previous work. For SSIM results, the proposed system still able to provide a promising result, although there were some of the output images produced lower results than the previous work.

3 Materials and Methods

3.1 Material

A total of 30 Ki67 astrocytoma digital pathology images have been captured at the Department of Pathology, Hospital Universiti Sains Malaysia (HUSM). These images were the “hot-spot” area images that have been selected from the histological slides. The “hot-spot” area is referring to the slide area of malignant cells with a high proliferative activity be potentially associated with a more aggressive biological behaviour that represented in the whole of the tumour [8]. Those tissue slides were prepared and stained from 2016 to 2018, which consist of different tumour staging. The Ki67 index and the tumour grading results for each slide were scored by the pathologists. In this study, the IHC staining was used to stain the tissue specimens. For slide staining, the positive Ki67 nuclei were stained using diaminobenzidine (DAB), while the haematoxylin was used to stain the negative Ki67 nuclei. The IHC staining caused the positive Ki67 cells to be appeared in granular brown colour, while negative Ki67 cells appeared in blue colour. The Ki67 images were captured under 40× magnification using an Olympus BX51 microscope and Cell^F software that worked as an interface to the digital camera that attached to the microscope. The sample images were then saved as (*.jpg) format with the resolution of 4140×3096 pixels and 24-bit RGB. Figure 1 shows a dataset of 30 astrocytoma images with different quality and illumination used for the analysis of this study.

3.2 Method

Generally, the automated enhancement system consists of three major steps, which are image resizing, colour space conversion, and image enhancement. There are different techniques for image enhancement but this study focused on contrast enhancement technique.

3.2.1 Image Resizing

At first, the proposed system resizes the sample images into new pixel dimensions. Large size, high resolution images can slow down the processing speed and require more storage space. Additionally, the number of cells used to be analysed for this study was reasonably large. Thus, it is necessary to have an algorithm that can optimize the processing speed and save storage space. In this study, the proposed system was set to resize the sample images into 1360×1024 pixels. The size is the lowest resolution without compromising the useful features of the Ki67 cells.

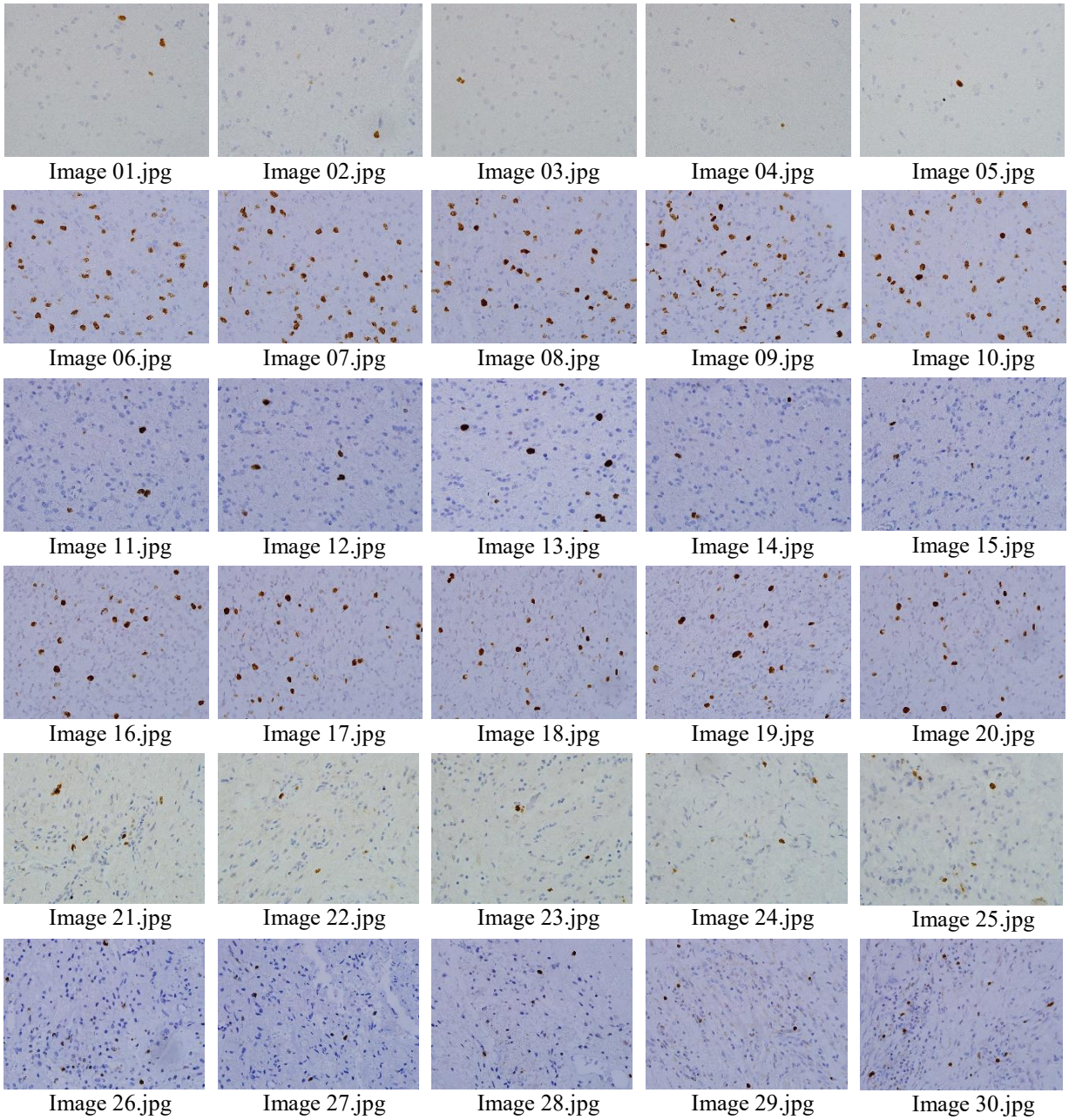


Figure 1: A dataset of 30 astrocytoma histopathological images

3.2.2 Colour Space Conversion

Medical images are usually associated with illumination problems. In the field of histology, this issue has been burdensome to pathologists since all the features, size, shape, and other morphological appearances of the cell structures are the critical indicators in determining the presence and severity of a disease. If the histopathological images have non-uniform illumination and poor contrast problems, it will affect the accuracy and effectiveness of any diagnosing analysis. For this reason, image enhancement is required to improve the quality of the sample images. To increase the contrast of the image, the colour space needs to be converted into a colour space that has the luminosity values as one of its components. For this study, the proposed procedure will convert the RGB colour space of the captured image into *L*a*b** colour space. This colour space was selected due to the exact representation of colour and is a device-independent colour model. Before converting to *L*a*b** colour space, the images need to be converted into CIEXYZ colour space first. The conversion from RGB colour space into CIEXYZ colour space was carried out using Equation 1 [9].

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4125 & 0.3576 & 0.1804 \\ 0.2127 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9502 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

Next, Equation 2 to 4 show the calculation from CIEXYZ colour space to *L*a*b** colour space [10]. X_n, Y_n, and Z_n are the tristimulus value of the reference white. *X*, *Y*, and *Z* describe as any colour that can be interpreted by an average human observer.

$$L^* = 116 \left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} - 16 \tag{2}$$

$$a^* = 500 \left[\left(\frac{X}{X_n}\right)^{\frac{1}{3}} - \left(\frac{Y}{Y_n}\right)^{\frac{1}{3}}\right] \tag{3}$$

$$b^* = 200 \left[\left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} - \left(\frac{Z}{Z_n}\right)^{\frac{1}{3}}\right] \tag{4}$$

3.2.3 Image Enhancement

This paper concentrating on enhancing the histopathological images of astrocytoma by using contrast enhancement techniques. Three common contrast enhancement techniques were applied in this study, which are contrast stretching, histogram equalization, and contrast-limited adaptive histogram equalization (CLAHE) technique. As mentioned in the previous section, the contrast enhancement techniques will be applied to the luminosity channel. In this study, all the enhancement process was based on one general equation [11]. This equation can be expressed as

$$I(x,y) = p(x,y)q(x,y) * \text{maximum } luminosity \tag{5}$$

where $q(x,y)$ can be calculated using the expression

$$q(x,y) = J(x,y) / \text{maximum } luminosity \tag{6}$$

$I(x, y)$ is the output of enhanced luminosity channel, $p(x,y)$ represents the new luminance value for pixel (x,y) after applying the contrast enhancement techniques, $q(x,y)$ is the processed luminance image, and $J(x,y)$ is the luminosity value at luminance channel. For this study, the luminosity values have been scaled to the range of [0, 1]. The issue raised in this study is the selection of maximum luminosity value. This is because the captured images have various illumination conditions. If the value is constant, it might affect the enhancement results. Based on the observation through the captured images, it is shown the poor quality images need a high luminosity value for enhancing the contrast, while good quality images just need a low luminosity value to enhance the contrast. Therefore, this study comes up with an automated luminosity value selection algorithm to determine the maximum luminosity value, which will be used with the enhancement technique algorithm. The algorithm is shown in Equation 7

$$maximum\ luminosity = avg(luminance)/[max(luminance) - min(luminance)] \tag{7}$$

where the *avg*(*luminance*) is the average of all luminosity values in L^* channel. The *max*(*luminance*) is the maximum value in the luminosity channel and the *min*(*luminance*) is the minimum value in the luminosity channel. Then, the resultant of the contrast enhanced image will be converted back to RGB colour space for visualization purpose.

- Contrast Stretching

This technique attempts to improve the contrast within an image by stretching the entire range of intensity values into a new desired range. The idea of this technique is to enhance the dynamic range of the grey levels in the image being processed [12]. A new maximum and minimum intensity value is required for executing the process. Equation 8 shows the formula for contrast stretching [13]:

$$p(x, y) = 255 * \left[\frac{q(x, y) - f_{min}}{f_{max} - f_{min}}\right] \tag{8}$$

where $p(x,y)$ is the new luminance value for pixel (x,y) and $q(x,y)$ is the luminance level from the processed luminance image. The f_{max} is the maximum luminance level value in the input image, while f_{min} is the minimum luminance level values in the input image.

- Histogram Equalization

Histogram equalization is another technique that can be used for enhancing the contrast of an image. The process is done by adjusting and spreading the luminance histogram of the captured image into a new histogram were all the luminance values will be equalized and have the same frequency. As shown in Equation 9, the output image can be obtained by mapping each pixel in the input image intensity (luminance) r_k into a corresponding pixel with level s_k in the output image [12].

$$s_k = T(r_k) = (L - 1)\sum_{j=0}^{k} p_r(r_j) \tag{9}$$

where the probability of occurrence of luminance level r_k, $p_r(r_j)$ can be calculated as

$$p_r(r_j) = \frac{n_k}{MN} \quad k = 0,1,2, \dots, L - 1 \tag{10}$$

where n_k is the number of pixels that have luminance level r_k, MN is the total number of pixels in the image, and L is the total number of possible luminance levels in the image. Note that, this paper used the symbol $p(x,y)$ (see Equation 5) to indicate the resultant image after applying the contrast enhancement techniques. Thus, all the s_k values will be transferred to the variable $p(x,y)$.

- Contrast-Limited Adaptive Histogram Equalization (CLAHE)

This technique is usually used to enhance the low contrast of medical images. The CLAHE technique is a variation of adaptive histogram equalization where the function to reduce the noise amplification problem by limiting the contrast amplification [14]. Instead of using the whole image, this technique is performed on small regions called as "tiles". The contrast of each tiles is enhanced, resulting the histogram of the output region approximately matches the histogram specified by the desired histogram value [11]. The procedure to perform the CLAHE technique was done by:

- Acquire the Ki67 histopathological image of astrocytoma.
- Get all input values used in the enhancement process like number of regions in row and columns direction separately, number of bin used in the histogram, cliplimit and distribution parameter type.
- Then the image is divided into non-overlapping regions ("tiles") that having an equal-size of $M \times N$. In this study, each "tiles" is set to have a size of 8×8.
- Histogram is extracted for each "tiles".
- Calculate the clip-limit value. The clip limit β can be calculated by using Equation 11 [15]

$$\beta = \frac{M}{N}\left(1 + \frac{\alpha}{100}(s_{max} - 1)\right) \tag{11}$$

where α is the clip factor that has range between 0 and 100. s_{max} is the maximum allowable slope, in which its value can be between 1 and s_{max} [15].

- The desired histogram for each "tiles" is clipped and renormalized.
- Generate the luminance level mapping and clipped histogram. Basically the region number of pixels are equally divided in each luminance levels. Therefore, the average number of pixels is calculated as [16]:

$$N_{avg} = \frac{N_{CR-XP} \times N_{CR-YP}}{N_{grey}} \tag{12}$$

where N_{avg} is the average number of pixels. N_{grey} is the number of luminance level in the contextual program. $N_{CR\text{-}XP}$ is referring to the number of pixels in X direction of contextual region. $N_{CR\text{-}YP}$ is the number of pixels in Y direction of contextual region.

- Calculate the actual cliplimit (N_{CL}) using the Equation 13:

$$N_{CL} = N_{clip} \times N_{avg} \tag{13}$$

where N_{clip} is the normalized clip-limit in the range of [0,1]. The histogram will be clipped once it exceeds its related clip-limit.

- Redistribute the clipped histograms values to all the histogram bins.
- Interpolate the luminance level mapping function to get a contrast enhanced image.

3.3 Quantitative Measures

Image Quality Assessment (IQA) is a test performed for measuring the level of accuracy of an image. The IQA is the quality assessment of a distorted image with respect to the original image [17]. The area of IQA can be divided into two areas which are full-reference evaluation (FR-IQA) and no-reference evaluation (NR-IQA). The FR-IQA is relying on the whole information of the original or reference image for evaluating the performance. The NR-IQA does not require a base image for evaluating the quality of an image. In this paper, the reference image is defined by the histological images of astrocytoma. The output enhanced images will be compared with those reference images for measuring the quality performance of the proposed system. Ten quantitative measures are carried out in this study. The

measurements comprise of entropy measurement (H), Absolute Mean Brightness Error (AMBE), Tenengrad Criterion (TEN), Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Root Mean Square Error (RMSE), Universal Image Quality Index (UIQI), Root-Mean-Square Contrast (RMS Contrast), Visual Information Fidelity (VIF), and Lightness Order Error (LOE).

- Entropy (H)

The entropy of the image tells about the amount of information contained within an image. The entropy of the enhanced images should not be lower than the entropy of the input image. Lower entropy conveys a loss of some image details. Higher values of entropy mean the image is rich in detail. However, it also considers image noise as image details and thus sometimes give a higher value even for noisy images. The entropy of an image can be calculated as [18]

$$H = -\sum p \times \ln(p) \tag{14}$$

where p is the histogram count for a segment of image.

- Absolute Mean Brightness Error (AMBE)

AMBE is the difference in the mean brightness of the input and output images. This analysis is used to measure the brightness preservation. A good brightness preserving method will have a low AMBE. The formula can be expressed as [19]

$$AMBE = |E(X) - E(Y)| \tag{15}$$

where $E(X)$ is the mean of original image and $E(Y)$ is the mean of contrast enhanced image.

- Tenengrad Criterion (TEN)

This technique is the most well-known benchmark image sharpness measure. This technique has been widely used to analyse whether structural information in the enhanced image has been improved or not. A higher value of TEN suggests sharper edges. The image quality is usually considered higher if its Tenengrad value is higher. TEN is calculated as [20]

$$TEN = \sum_x \sum_y S(x,y)^2, \qquad for\ S(x,y > T) \tag{16}$$

where $S(x,y)$ is the gradient magnitude of an image (x,y), and T is the threshold value.

- Structural Similarity Index (SSIM)

The SSIM quantifies the structural loss based on statistical moments. SSIM measure combines luminance, contrast, and structural comparisons. It is a method for measuring the similarity between two images. SSIM is based on visible structures in the image. The resulting performance index takes values between -1 to 1. The maximum value of 1 is achieved when x and y are identical. SSIM can be calculated via the following formula [21]

$$SSIM(x,y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma} \tag{17}$$

where

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}, \tag{18}$$

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}, \tag{19}$$

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \tag{20}$$

where $\mu_x\mu_y$, $\sigma_x\sigma_y$, and σ_{xy} are the local means, standard deviations, and cross-covariance for image (x,y). $l(x,y)$, $c(x,y)$, and $s(x,y)$ are the luminance term, contrast term and the structural term. C_1, C_2, and C_3 are the small constant values to avoid division by zero problem.

- Peak Signal-to-Noise Ratio (PSNR)

PSNR is an expression for the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation. The ratio is used as a quality measurement between the original and enhanced images. The higher the PSNR, the better the quality of the output image. As shown in Equation 21, the calculation of PSNR is usually expressed in decibels [22].

$$PSNR = 10\ \log_{10}\left(\frac{R^2}{MSE}\right) \tag{21}$$

where R is the maximum fluctuation in the original image data type, and MSE is the mean square error between contrast enhanced image with reference image.

- Root Mean Square Error (RMSE)

RMSE is a measure of accuracy. The RMSE is a well-known parameter for measuring the quality of an enhanced image by calculating the average magnitude of the error. RMSE is frequently used to measure the difference between values predicted by an estimator and the values observed from the thing being modelled or estimated. The RMSE can be calculated by taking the square root of Mean Square Error (MSE). A higher RMSE indicates a greater difference between the original and processed image. Equation 22 shows the formula to calculate the RMSE of enhanced image [23]:

$$RMSE = \sqrt{\frac{1}{PQ}\sum_{i=1}^{P}\sum_{j=1}^{Q}[x(i,j) - \hat{x}(i,j)]^2} \tag{22}$$

where $x(i,j)$ is the discrete image mapping, $\hat{x}(i,j)$ is the enhanced and reconstructed mapping. P and Q are referring to the number of rows and columns in the input image.

- Universal Image Quality Index (UIQI)

The UIQI is a model for quantifying image distortion between the original image with the reference image. The UIQI is the product of three components, which are loss of correlation, luminance distortion,

and contrast distortion. The values vary from -1 to 1. The greater the similarity between the two images will be achieved when the UIQI value is closer to one. UIQI is defined as [24]

$$UIQI = \frac{4\sigma_{XY}\,\bar{X}\bar{Y}}{\left(\sigma_x^2 + \sigma_y^2\right)\left[(\bar{x})^2 + (\bar{y})^2\right]} \tag{23}$$

where $\bar{x}$ and $\bar{y}$ are the mean of image *X* and image *Y*, σ_x^2 and σ_y^2 are the variance of image *X* and image *Y*, and σ_{XY} is the standard deviation.

- Root-Mean-Square (RMS) Contrast

There are several ways to measure the contrast of an image, such as Michelson Contrast, Weber-Fechner Law, and RMS Contrast. Like Michelson Contrast, this measurement is suitable to be applied to the images that have equivalent bright and dark features, like sinusoidal gratings (18). For Weber-Fechner Law measurement, it was recommended to use when small features are present on a large uniform background, like letter stimuli. In this study, the RMS Contrast was selected for the analysis measurement as it is suitable for images with complex patterns, such as natural images. The RMS Contrast refers to the standard deviation of the pixel intensities. The RMS Contrast can be calculated by using Equation 24 as [25]

$$rms = \left[\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2\right]^{\frac{1}{2}} \tag{24}$$

where

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{25}$$

where x_i is a normalized grey-level value between 0 to 1 and $\bar{x}$ is the mean normalized grey level. Higher values of RMS Contrast indicate the image has better contrast.

- Visual Information Fidelity (VIF)

In 2006, Sheikh and Bovik [26] had developed an image quality algorithm to measure the loss of image information, called Visual Information Fidelity (VIF). The VIF analysis used two quantities for assessing the image quality. First, the information shared by the reference image, and second was the data obtained by extracting the reference information from the distorted image. The VIF utilizes the wavelet decomposition to measure the mutual information between the reference and distorted images [27]. The compiled mutual information will be used to determine the ratio and generate the overall assessment results. The processed image is said to be identical if the value was equal to 1. If the value is less than 1, it signifies a loss of visual quality in the processed image or degraded. For VIF value greater than 1, it indicates the quality of the original image has been enhanced.

- Lightness Order Error (LOE)

The naturalness of an image is necessary for assessing a high-quality image. This naturalness is defined as the degree of correspondence between images and the human perception of reality. LOE analysis is another assessment that can be implemented to measure the quality of an image. This method was proposed by Wang *et al.,* [28] to measure the naturalness preservation in the enhanced image. The proposed method consists of three parts. First, the bright pass filter is used to separate the reflectance and illumination of the original image. Second, the proposed method used the bi-log transformation to process this illumination. Third, the enhanced image is obtained by synthesizing the reflectance and the mapped illumination. Small

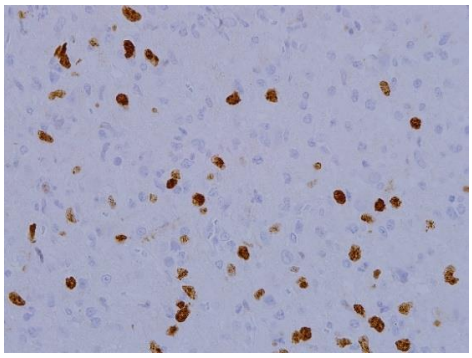
LOE values suggest that the naturalness of the enhanced image is well preserved relative to the original image [29].

4 Result and Discussion

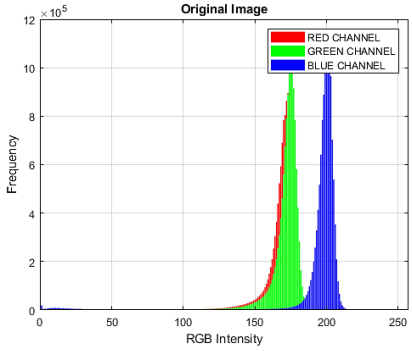
All the contrast enhancement methods are carried out by using MATLAB version 2018 and a personal computer that runs on Intel Core i7-5500U, 2.4GHz, and 16GB RAM. There were 30 Ki67 images of astrocytoma that have been tested in this study. Three contrast enhancement techniques have been applied in this study. The contrast-enhanced images from each technique were compared with the original images for measuring the performance of each enhancement technique. Ten quantitative measures have been calculated for identifying the best technique for enhancing the contrast of astrocytoma microscopic images. Figure 2 shows the comparison of resultant images after applying three different image enhancement techniques with the RGB histograms.

Generally, from the visual observation in Figure 2, the resultant enhancement images have shown improvement, especially in the contrast of the Ki67 cells, which has been increased compared to the original image. Figure 2(a) shows an example of a Ki67 image of astrocytoma. The positive Ki67 cells (red-brownish coloured cells) can be seen clearly from the original image, while there were some negative Ki67 cells (blue coloured cells) had a low colour intensity and some of them are difficult to visualize. Figure 2 (c), (e), and (g) illustrate the processed image after applying the automated enhancement techniques. After applying the contrast enhancement techniques, the morphological of all cells was improved and visible. The enhancement results also showed that the texture, size, and shape of the cells were expressed clearly. However, as illustrated in Figure 2(g), some image regions are over-enhanced, where the resultant image appeared deep darkened compared to other enhanced images.

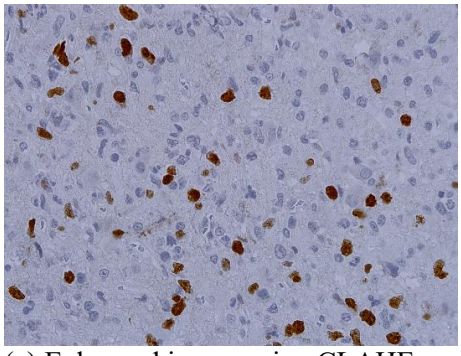
An image histogram can be used to describe the tonal distribution in a digital image. The histogram illustrates the number of pixels in an image at each different intensity value found in the image. A broad histogram indicates the image has good contrast, while a narrow histogram reflects the image has low contrast, which the image might appear flat or dull.



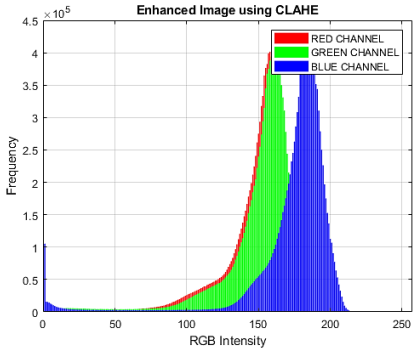
(a) Original Image



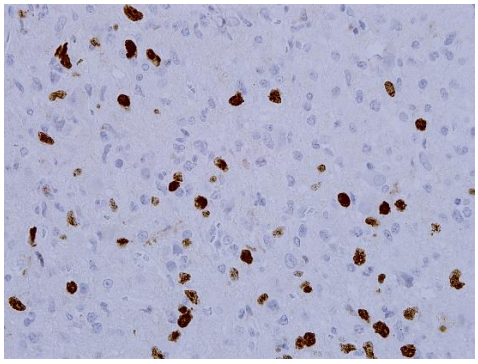
(b) RGB histogram of original image



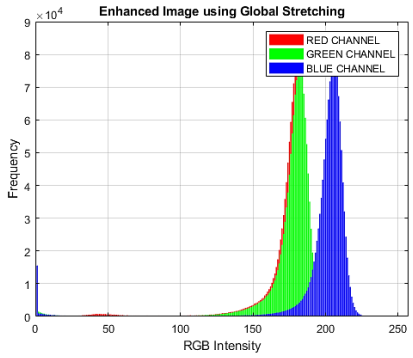
(c) Enhanced image using CLAHE technique



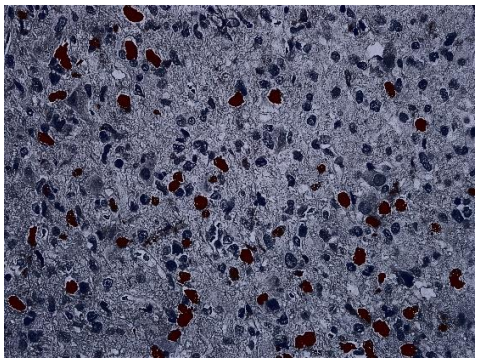
(d) RGB histogram of enhanced image using CLAHE



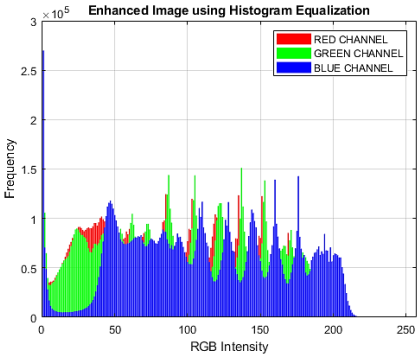
(e) Enhanced image using Contrast Stretching technique



(f) RGB histogram of enhanced image using Contrast Stretching



(g) Enhanced image using Histogram Equalization technique



(h) RGB histogram of enhanced image using Histogram Equalization

Figure 2: Comparison of RGB histograms between original images with enhanced images

Figure 2 also showed the comparison of colour histograms between the original images with enhanced images. The colour histogram represents the number of pixels in each RGB channel. From Figure 2(b), the histogram of all RGB channels showed there are no values between 50 to 100. The intensity for all channels was mostly concentrated to the middle portion of the range, which on an average between 100 to 220. Compared with others, the histogram in Figure 2(d) showed a well-enhanced histogram, where the histogram for all RGB channels became wider. The intensity values also were well-spread and filled the entire intensity range. As shown in Figure 2(h), the histogram for all RGB channels were equalized. Although the range of the histograms became wider, it is shown the majority of the pixels were shifted to the left of centre of the graph. This signifies there will more dark and shadow areas will be produced in the output image. Hence, the analysis towards the desired features became more challenging, since the image was under underexposed condition. The details results of analysis performance for three proposed enhancement techniques are demonstrated in Table 1.

Table 1: Comparison Average Values of Ten Quantitative Measures Based on Different Contrast Enhancement Techniques against 30 Astrocytoma Images

Quantitative Measurement	CLAHE	Contrast Stretching	Histogram Equalization
H	5.996	5.630	**6.310**
TEN	5916.63	12017.33	**65976.79**
AMBE	15.249	**13.449**	69.667
SSIM	**0.790**	0.754	0.231
PSNR (dB)	**22.414**	22.056	9.278
RMSE	**0.969**	4.468	3.044
UIQI	**0.983**	0.964	0.695
RMS Contrast	0.628	**0.650**	0.471
VIF	1.360	**1.475**	1.079
LOE	718.453	**709.624**	805.723

The best value is highlighted in bold.

Table 1 showed the average calculated results of seven quantitative measures based on 30 astrocytoma images. From the table, the histogram equalization technique had the highest value of entropy with an average of 6.310. This showed an improvement in the quality of the images. The increment of the entropy value in the enhanced images indicates the details of the information and visibility of the original images was improved. For TEN analysis, the histogram equalization had the highest average value. This signifies the objects in the enhanced images have maximum edge sharpness and the structural information from the original images was also improved. However, based on the visual appearance in Figure 2(g), it showed the noise was also enhanced with the edges of the input images. Next was the AMBE analysis. It was shown only CLAHE and contrast stretching techniques gave acceptable results. The average AMBE value showed that the contrast stretching was the best preserves the image brightness. The brightness was well-preserved with an average AMBE value of 13.449, which much lower than all other methods.

For the SSIM test, the table showed the CLAHE technique gave the highest average value with 0.790. This value signified the image structures of the enhanced images were well preserved. Rationally, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Based on Table 1, the CLAHE technique produced the highest average PSNR values among other techniques with an average of 22.414dB. This value indicates the enhanced images have less noisy signal and these images are relatively high quality. According to the given average RMSE values in Table 1, it was shown that the CLAHE technique produced the lowest RMSE value among other techniques with an average of 0.969. This value conveys the difference between the original inputs images with the enhanced images are smaller since the error value is lowest compared to other techniques. Following the results of UIQI, the CLAHE technique has the highest average value with an average of 0.983. This value suggests that the quality of enhanced images by using the CLAHE technique is better than other techniques.

For RMS contrast analysis, the values produced by using the CLAHE and contrast stretching higher and acceptable. These values indicate the contrast of the enhanced image has been improved relative to the original image. The following test was VIF measurement. According to the results shown in Table 1, the contrast stretching produced the highest results in VIF compared to other techniques, with an average of 1.475. This signifies the quantity of data image information loss from the processed image was fewer than other techniques. Finally was the LOE analysis. As explained in Section 3.3, the LOE measures the naturalness preservation in the enhanced images. From Table 1, the contrast stretching had the lowest LOE value, with an average of 709.624. Thus, this value suggests the naturalness of the enhanced images are well preserved by using this technique.

5 Conclusion

This study presents an automated image enhancement algorithm for improving the astrocytoma histopathological images. Three different contrast enhancement techniques were tested in this study. These contrast enhancement techniques involve CLAHE, contrast stretching, and histogram equalization techniques. For measuring the quality of each image enhancement techniques, ten quantitative measurements were applied to the enhanced images. Based on the analysis, it reveals that only CLAHE and contrast stretching give acceptable results in improving the quality of the original images. The findings result also showed each of these two techniques has its own advantages. The contrast stretching technique showed that this technique was better in brightness preservation, minimum loss of image information, contrast enhancement, and the naturalness of an image. For the CLAHE technique, it produces good results in image quality measurement, image similarity measurement, image accuracy measurement, and minimum distortions to the enhanced images.

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References

1. Goodenberger ML, Jenkins RB. Genetics of adult glioma. Cancer Genetics. 2012.
2. Shirazi SH, Naz S, Razzak MI, Umar AI, Zaib A. Automated pathology image analysis [Internet]. Soft Computing Based Medical Image Analysis. Elsevier Inc.; 2018. 13–29 p. Available from: http://dx.doi.org/10.1016/B978-0-12-813087-2.00026-9
3. Kaur A, Singh C. Contrast enhancement for cephalometric images using wavelet-based modified adaptive histogram equalization. Appl Soft Comput J [Internet]. 2017;51:180–91. Available from: http://dx.doi.org/10.1016/j.asoc.2016.11.046
4. Muhimmah I, Wijaya DP, Indrayanti. Color Swapping to Enhance Breast Cancer Digital Image Qualities Using Stain Normalization. In: IOP Conference Series: Materials Science and Engineering. 2017.
5. Pandey P, Jain S, Khatri SK. Enhancement of medical images using Kalman filter. In: 2017 6th International Conference on Reliability, Infocom Technologies and Optimization: Trends and Future Directions, ICRITO 2017. 2018. p. 619–623.
6. Kumar TG, Asha V, Manish TI, Muthulakshmi G. Empirical System of Image Enhancement for Digital Mircroscopic Pneumonia Bacteria Images. Brastislava Med J. 2018;119(8):522–529.
7. Singh A, Chandra A, Kumar R, Singh K, Dey N. Dark Channel Processing for Medical Image Enhancement. In: 2019 IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE). IEEE; 2020. p. 1–6.
8. Fulawka L, Halon A. Ki-67 evaluation in breast cancer: The daily diagnostic practice. Indian J Pathol Microbiol [Internet]. 2017;60(2):177–84. Available from: http://www.ijpmonline.org/text.asp?2017/60/2/177/208409
9. Kaur A, Kranthi B. Comparison between YCbCr Color Space and CIELab Color Space for Skin Color Segmentation. Int J Appl Inf Syst. 2012;3(4):30–33.
10. Tkaleie M, Tasie JF. Colour spaces - Perceptual, Historical and Applicational Background. IEEE Reg 8 EUROCON 2003 Comput as a Tool. 2003;2:304–308.
11. Mathworks. Contrast Enhancement Techniques [Internet]. Mathworks Documentation. 2020 [cited 2020 Feb 11]. Available from: https://www.mathworks.com/help/images/contrast-enhancement-techniques.html
12. Gonzalez RC, Woods RE. Digital Image Processing (3rd Edition). Prentice-Hall, Inc. Upper Saddle River, NJ, USA ©2006. 2007.

13. Kaur J, Choudhary A. Comparison of Several Contrast Stretching Techniques on Acute Leukemia Images. Int J Eng Innov Technol. 2012;2(1):332–335.
14. Pizer SM, Amburn EP, Austin JD, Cromartie R, Geselowitz A, Greer T, et al. Adaptive histogram equalization and its variations. Comput Vision, Graph Image Process. 1987;39(3):355–368.
15. Al-Ameen Z, Sulong G, Rehman A, Al-Dhelaan A, Saba T, Al-Rodhaan M. An innovative technique for contrast enhancement of computed tomography images using normalized gamma-corrected contrast-limited adaptive histogram equalization. EURASIP J Adv Signal Process. 2015;
16. Yadav G, Maheshwari S, Agarwal A. Contrast limited adaptive histogram equalization based enhancement for real time video system. Proc 2014 Int Conf Adv Comput Commun Informatics, ICACCI 2014. 2014;2392–2397.
17. Al Madeed N, Awan Z, Al Madeed S. Image Quality Assessment - A Survey of Recent Approaches. In: 8th International Conference on Computer Science, Engineering and Applications. 2018. p. 143–156.
18. Gupta S, Porwal R. Appropriate Contrast Enhancement Measures for Brain and Breast Cancer Images. Int J Biomed Imaging. 2016;2016(1).
19. Chen S Der, Ramli AR. Preserving brightness in histogram equalization based contrast enhancement techniques. Digit Signal Process A Rev J. 2004;14(5):413–428.
20. Gelman L. Advances in Electrical Engineering and Computational Science. Lecture Notes in Electrical Engineering. Springer Science & Business Media; 2009.
21. Wang Z, Bovik AC, Sheikh HR, Simoncelli EP. Image quality assessment: From error visibility to structural similarity. IEEE Trans Image Process. 2004;13(4):600–612.
22. Deshmukh K, Pollett C. Residual CNN Image Compression. In: Advances in Visual Computing: 14th International Symposium on Visual Computing, ISVC 2019. 2019. p. 317–382.
23. Morales-Mendoza LJ, Shmaliy YS, Ibarra-Manzano OG. Enhancing Ultrasound Images Using Hybrid FIR Structures. In: Image Processing. Rijeka, Croatia: Book on Demand; 2009. p. 287–310.
24. Wang Z, Bovik AC. A universal image quality index. IEEE Signal Process Lett. 2002;
25. Peli E. Contrast in complex images. J Opt Soc Am A. 1990;7(10):2032.
26. Sheikh HR, Bovik AC. Image information and visual quality. ICASSP, IEEE Int Conf Acoust Speech Signal Process - Proc. 2004;3(2):430–444.
27. Kuo TY, Su PC, Tsai CM. Improved visual information fidelity based on sensitivity characteristics of digital images. J Vis Commun Image Represent [Internet]. 2016;40:76–84. Available from: http://dx.doi.org/10.1016/j.jvcir.2016.06.010
28. Wang S, Zheng J, Hu HM, Li B. Naturalness preserved enhancement algorithm for non-uniform illumination images. IEEE Trans Image Process. 2013;22(9):3538–3548.
29. Qureshi MA, Beghdadi A, Deriche M. Towards the design of a consistent image contrast enhancement evaluation measure. Signal Process Image Commun [Internet]. 2017;58(August):212–27. Available from: http://dx.doi.org/10.1016/j.image.2017.08.004