Journal of Chemical Health Risks

www.jchr.org

JCHR (2024) 14(1), 1183-1196 | ISSN:2251-6727

A Hybrid Approach To Image Enhancement In Digital Histopathology

Karishma Rao[1*], Dr. Manu Bansal[2], Gagandeep kaur[3]

[1*,2]Thapar Institute of Engineering & Technology, Patiala, India
Email: Karishmar.93@gmail.com[1*], mbansal@thapar.edu[2,]
[3]Thapar Institute of Engineering & Technology, Patiala, India Email: gagandeep@thapar.edu3

***Corresponding author -** Karishma Rao
[2]Thapar Institute of Engineering & Technology, Patiala, IndiaEmail: Karishmar.93@gmail.com
(Received: 27 October 2023 Revised: 22 November Accepted: 26 December)

KEYWORDS
Contrast Limited Adaptive Histogram Equalization (LHE), Contrast, Saturation, Universal image quality index (UIQI), retinex theory

ABSTRACT:
Purpose Numerous clinicians utilise digital histopathology images to diagnose diseases such as cancer and to get information about the aetiology of the illness. Typically, histopathology images exhibit poor image quality artefacts such as low contrast across various areas of the image, blurring, and inadequate lighting. The primary objective of this article is to offer a better and successful hybrid strategy for delivering overall contrast enhancement, accurately enhancing fine details, and producing a natural and distortion-free histopathological image.
Methods The novel hybrid method leverages the advantages of many established enhancing approaches to generate a natural and distortion-free histopathology picture from low-quality histopathology photos. After obtaining the brightness channel using a luminance measurement technique, two inputs are created utilising local histogram equalisation and retinex theory. The brightness component is changed by fusing the derived inputs with their neighbouring weights on a multi-level basis. Through a careful selection of inputs, their neighbouring weights, and a multi-level fusion technique. An extensive quantitative analysis demonstrates that the proposed method outperforms existing image enhancement techniques. The proposed method produced a maximum average peak signal-to-noise ratio of 29, a maximum average UIQI, SSIM, and FSIM of 0.99, 0.93, and 0.96, respectively, and a minimum average AMBE of 2.22.
Results The proposed approach was able to give superior overall improvement while preserving naturalness and superior performance in all performance measures such as AMBE, SSIM, FSIM, UIQI, and PSNR.
Conclusion The proposed approach produces images of higher quality, which is extremely beneficial for disease inspection and diagnosis.

1. Introduction

Numerous clinicians utilise digital histopathology images [1] to diagnose disorders or cancer and also give valuable information about the disease's aetiology. Generally, histopathological images exhibit poor picture quality artefacts such as low contrast across various sections of the image, blurring, and inadequate lighting [2]. These artefacts are caused by incorrect straining procedures, an incorrect camera configuration, and other difficulties. Histopathology images need adequate augmentation of picture features such as contrast, borders, edges, and brightness in order to move them to a condition suitable for processing by a clinical expert or person. This preprocessing phase is also necessary to improve the accuracy of several computer-aided techniques used in histopathology pictures, such as segmentation and classification.

Enhancing low contrast histology images is a critical step in the study of histopathology images. It is a technique for adjusting the picture's intensities in order to get the desired image contrast and brightness tone for the best histopathological image quality [3]. Numerous conventional picture enhancing methods are documented in the literature. These strategies may be thought of as spatial and transfer-based enhancements. The former use the mapping function to directly convert all of the image's intensities. It includes of approaches based on histograms, such as histogram-based augmentation strategies [3-17]. The latter involves transforming spatial data to other domains and then processing the transfer domain to generate the

Journal of Chemical Health Risks

www.jchr.org

JCHR (2024) 14(1), 1183-1196 | ISSN:2251-6727

output picture; it comprises wavelet-based enhancement techniques [22-25].

The issue with typical enhancement approaches is that although each method improves a few performance parameters, it does so at the expense of other critical performance matrices and results in unwanted picture quality distortion. To provide additional clarity, one low-enhanced histopathology image is proposed using the five most widely used existing enhancement methods (THE [3,4], LHE [4], DHE [9], MSR [26], and AGCW [17]), and these are experimentally evaluated using five critical performance matrices, including the Absolute mean brightness error (AMBE), Feature similarity index (FSIM), Structure similarity index (SSIM), Universal image quality index (UIQI) [25] as shown in Figure 1. Histogram Equalization (HE) is one of the most extensively used histogram-based procedures [4], and it enhances the picture by altering the histogram's pixel counts as seen in Figure 1(b). However, this technique results in an excessively enhanced histopathological picture with a high AMBE value, a poor similarity index (SSIM), and a low signal to noise ratio (PSNR). Another often used local enhancement approach is contrast restricted adaptive histogram equalisation (LHE) [4], which produces an unnatural-looking final picture with a low PSNR [12] and a low feature similarity index (FSIM) as shown in Figure 1(c). Adaptive gamma-based HE (AGCW) [17] is an upgraded variant of classic HE that produces a whitewashed histopathological picture with a high AMBE, a low universal quality index (UIQI), and a high noise content (PSNR) as seen in Figure 1(d). The most often used retinex-based technique is Multi-scale retinex (MSR) [26], which produces a color-distorted augmented picture with low similarity indexes such as UIQI and SSIM as shown in Figure 1(e). Another enhanced HE approach is dynamic histogram equalisation (DHE) [9], which enhances contrast but suffers from other critical quality matrices such as poor feature similarity, high AMBE, and low PSNR value as seen in Figure 1(f).

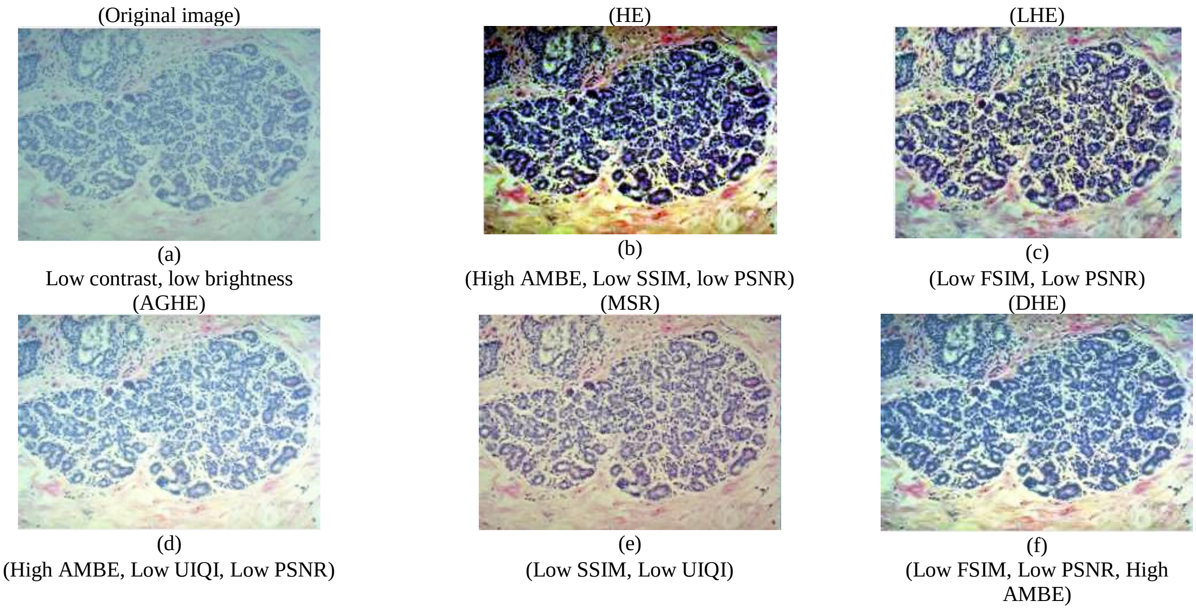


Fig. 1 (a) original image, (b) HE image, (c) LHE image, (d) AGHE image, (e) MSR image, (f) DHE image

The primary objective of this paper is to develop an improved and effective integrated fusion approach that incorporates the advantages of various mature image enhancement techniques in order to produce a natural and distortion-free histopathology image while also optimising all performance parameters. To compare the suggested method's performance to that of other established standard methods, other established standard methods are also run.

The remainder of the essay is structured as follows: Section 2 summarises previous research in the literature. Section 3 illustrates the suggested technique of augmentation. Section 4 outlines the performance parameters that will be used to interpret the experimental results. Finally, Section 5 has a concluding paragraph followed by a list of references.

2. Related work

There are numerous image enhancement approaches introduced by analyzers in the literature. The traditional histogram equalisation (THE) technique is still one of the most commonly used techniques for improving global contrast. The main idea of HE is subjected to input image pixel distribution over the entire dynamic

range based on limited cumulative values. Indeed, the entire image is divided into nearest levels that describe various image boundaries. To obtain a uniform histogram, the boundaries specifying the initial values are improved by admitting a couple of new boundaries within the previous one, and the incoming boundaries are defined recursively. However, standard histogram equalization resulted in excessive enhancement in the majority of the test images. To address these issues, various improved histogram-based enhancement approaches are introduced, including brightness preserving bi histogram equalisation (BPHE) [6], dualistic image histogram equalisation (DSHE) [7], Dynamic histogram equalization[9], minimum mean brightness error bi histogram equalisation [8], and recursively divided and summed HE approach [10-11]. All of these methods divide the incoming histogram into two parts based on average or central value, and the remaining methods separate the histogram recursively.

Because the above-improved histogram-based algorithms divide an image histogram into small sub-blocks and apply the HE algorithm to each small portion. These methods can provide overall global enhancement, but the resulting images lack local detail enhancement. Tan et al. developed a local histogram-based method for increasing the contrast of CT brain images [15]. The basic idea behind this algorithm is to divide the incoming image into numerous sub-portions. The grey level histogram pattern is rejected for each sub-portion and thus readjusted to the remaining grey levels with a selected threshold. Finally, we have a gray-level remapping function. One disadvantage of this method is the user-defined threshold value. Ameen et al. [14] proposed enhancing the contrast of CT images using a contrast restricted adaptive histogram equalisation (LHE) approach based on normalised gamma correction. The novel feature added to the preceding technique is a first stage with a normalised gamma correction feature. Huang and Yeh et al. presented a two-part histogram-based image enhancement method. The first section includes the division of the input histogram into small visible details. The second part involves grey level transformation for later contrast improvement of the image with full brightness preservation for each generated small histogram [16]. Huang et al. described a method that combines the standard gamma correction technique with histogram equalization. [17]. In comparison, the retinex-theory-based Multi-scale Retinex with Color Restoration (MSR)[26] iused the single-scale Retinex (SSR) to calculate the reflectance of an image by eliminating the illumination from the original image and then the final image is obtained by a weighted combination of different SSR outputs.

SVD approaches are also used to improve image contrast while avoiding the drawbacks of traditional methods [12, 13]. The singular value matrix contains the image's grey level data, so that changing the singular values directly affects the image's contrast, while the remaining information in the image remains unchanged. Bhandari et al. introduced the DWT-SVD-based approach for satellite image enhancement [14] to protect edge data from loss. In this method, the SVD method is only applied to the LL sub-band obtained via DWT. By varying the initial singular values by a correction factor, an improved lower sub-portion is obtained.

For contrast enhancement, Atta et al. proposed an improved approach based on DWT and SVD (ASVD) [18]. In fact, the authors used equalization to determine the enhanced singular matrix by combining the singular matrices of the original and output images. The method provides improved output without the formation of artefacts and improves the original mean brightness. X. Fu et al. [19] proposed a new remote sensing image enhancement method that first used regularised histogram equalisation to obtain better global enhancement and then used discrete cosine transform (DCT) to highlight the local details of an image. Koh et al. [20] described a method for improving the contrast of CT images using recursive sub-image histogram equalization in the transfer domain. However, gamma-based enhancement methods result in over-enhancement, especially when images' grey levels are not uniformly illuminated. Huang et al. [17] used the adaptive gamma correction with weightd disyrubution (AGCW) method to do not change the intensity level range and thus this technique does not give to the gamut-problem. Rao et al. [25] proposed novel image enhancement methods in which they first modify the histogram [15], then divide it into smaller histograms, clip each histogram, and finally apply bilateral filtering. Sahnoun et al. reported a method to improve spinal cord MRI images using both adaptive gamma transformation and DWT-SVD (DWT-AGC)[21]. The author first improves the lower frequency sub-bands of the MRI image by modifying the singular values, and then the adaptive gamma correction method is used to further improve the lower frequency sub-bands. Despite the fact that these approaches may conserve more average brightness than histogram-based approaches, they may fail to improve contrast. Sahnoun et al developed a method for medical images that defined the new gain factor based on DWT-SVD based computation to scale the singular value matrix.[22] Subramani et al. [23] suggested a three-stage medical image enhancement process: To begin, the input histogram is split into two histograms depending on the exposure threshold in order to maintain the mean brightness and then clipped to restrict contrast

Journal of Chemical Health Risks

www.jchr.org

JCHR (2024) 14(1), 1183-1196 | ISSN:2251-6727

amplification, and each clipped sub histogram is given a new dynamic range. Finally, a contrast-enhanced picture is obtained by independently equalising each clipped sub-histogram. Kumar et al. [31] implemented a new triple clipped histogram technique (THE-DWT) for improving the fundamental characteristics of clinical photographs, including brightness preservation and contrast. Triple clipped dynamic histogram equalization method is used to equalize the input medical image in the first step. Fundamental calculation-based fusion techniques, such as DWT-SVD, are used to modify the approximated and informational components of both equalized and original images. Acharya and Kumar [32] have proposed a strategy for improving the contrast of medical images that combines a genetic procedure, histogram subdivision, and probability density function (PDF). The threshold value is optimized according to the principles of genetic algorithms, which improves the adaptability of the proposed procedure. Rao et al. [33] proposed a new morphological transform method that uses particle swarm optimization, DWT-SVD, and edge map methods to improve the noise and contrast of CT images.

3. Methods

3.1. Proposed technique

The suggested blended enhancement approach works on the principle of fusing diverse entering inputs with their derived weights to provide a balanced improved output. Figure 2 depicts the suggested method's block diagram.

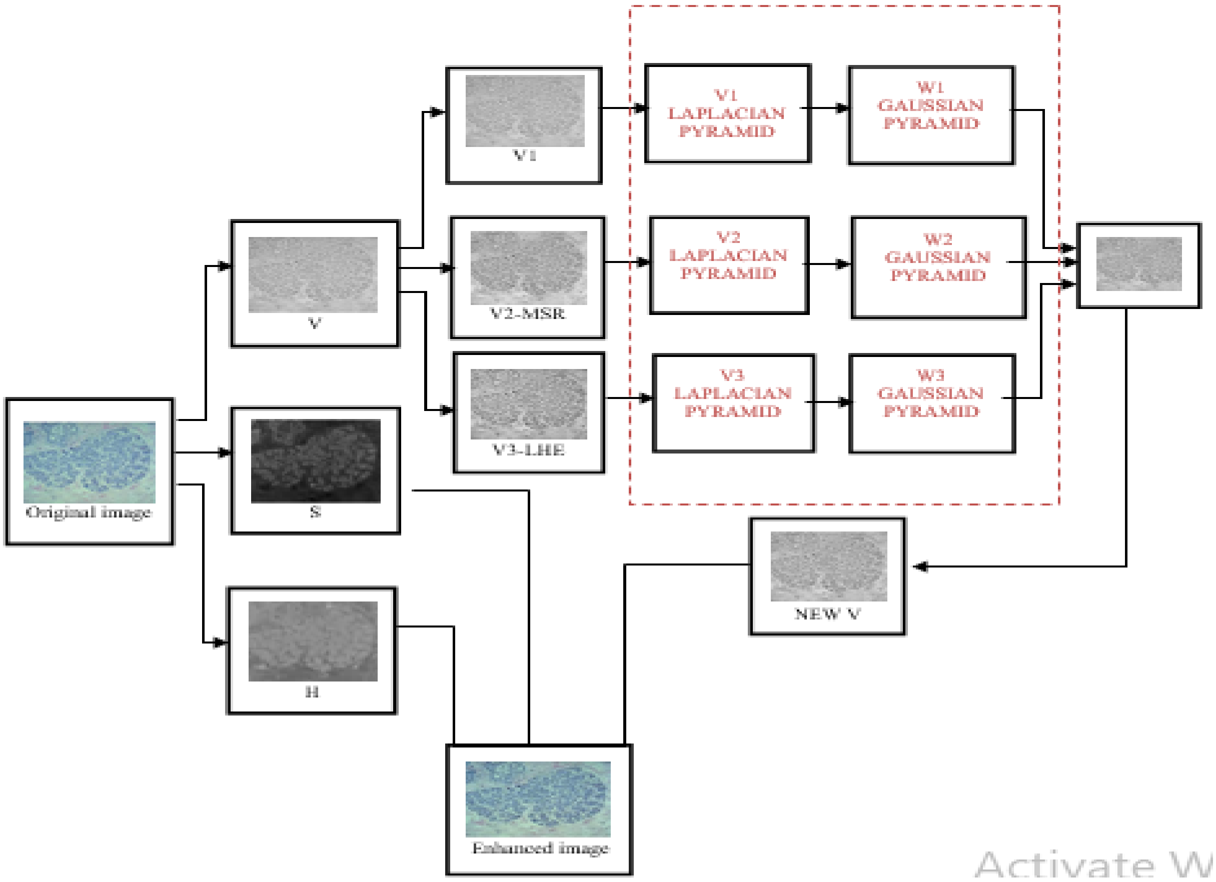


Fig. 2 Block diagram of the proposed scheme

The whole process has been broken down into four stages. To begin, the original picture is separated into three components: hue (H), saturation (S), and value (V). To improve the histopathology picture, only the V channel is treated further, and three inputs are created from the V component after LHE and MSR processing. Each derived input is converted to a weight matrix. The Laplacian pyramid is used to further process the inputs, while the Gaussian pyramid is used to breakdown the weights in order to fuse them together. After obtaining the final improved V component, it is combined with the remaining H and S components to provide the final enhanced output. Each stage is thoroughly discussed in the entering section.

Journal of Chemical Health Risks
www.jchr.org
JCHR (2024) 14(1), 1183-1196 | ISSN:2251-6727

3.2. Luminance channel estimation

In general, the RGB colour model may be used to depict colour digital histopathology pictures. If the suggested approach is applied directly to these three RGB colour space elements: Red (R), Green (G), and Blue (B), it may result in undesirable colour distortion owing to the various levels of change in these three components. To resolve this grave issue, the HSV colour model is being employed. The HSV space is more intuitive, since the hue (H) channel corresponds to the spectral structure of colour, the saturation (S) channel to the clarity of colours, and the value (V) channel to the lustre or brightness value. Hue and saturation refer to the image's colour content, while V refers to the image's brightness or luminance value. To begin, the RGB colour picture must be converted to HSV [17] to avoid colour distortion and artificial colour tone augmentation.
The following equations explain the conversion of an image's RGB space to HSV values.

Finally, the values of H, S, and V are computed using the equations (1) to (6).
The following equations were used to convert HSV to RGB: (7) to (13)

1. When H is in the range of 0◦ to 120◦, the RGB components are obtained by
2. When H is in the range of 120◦ to 240◦, the RGB components are obtained by
3. When H is in the range of 240◦ to 360◦, the RGB components are obtained by

3.3. Inputs calculation

Three input pictures are created from the estimated value component in the proposed blended-based technique (V). The first input picture is the value (V) component that was determined initially. This holds the original picture's brightness information, which enables us to avoid image distortion and keep the image's naturalness. The second input picture is used to compute the global overall enhancement, which brightens and suitably enhances the whole image, but notably the dark and low contrast areas prevalent in histopathological photos. Numerous approaches for global improvement are available, including histogram equalisation (HE) methods [3-16], gamma correction [18], and retinex-based methods [21]. The second input is calculated using the Multiscale retinex (MSR) technique on the predicted V channel in this approach. MSR is a composite of Single Scale Retinex (SSR) outputs [21] and is calculated by subtracting the light component from the picture to produce the reflectance. This is specified in Equation No (14)
Where is the number of scales, denotes the weighting factor for each scale, and denotes the output of the single-scale retinex for each scale and it is given in equation no (15)
Where is the value channel, is the convolution operator and is Gaussian filter which is written in equation (16)

In the proposed method, is set to 3, are 15, 80, and 250 and is 1/3. Because the grey level range is enlarged worldwide as a result of the luminance channel improvement, the contrast between nuclei and surrounding tissue is lowered or remains unchanged. As a result, the third input picture is identified using Contrast Limited Adaptive Histogram Equalization (LHE) [4], which enhances minor features within pathological images. LHE is applied directly to the channel with the predicted brightness (V). LHE stands for local frequency histogram enhancement and is defined as follows. The input luminance channel picture is first partitioned into a number of non-repeated areas of equal size. The next step is to extract the clip value from the input picture and fill in the image's borders before segmenting it into blocks if required. Each block's frequency graph is clipped to the appropriate clip limit. Finally, one of the interpolation algorithms is used to interpolate the grey level mappings. The input channel is separated into non-overlapping 8*8 blocks with a clip limit of 0.001.

3.4. Weights derivation

Following the calculation of three inputs from a single estimated luminance channel, the next step is to compute weights for the three inputs. Fu et al. [26] describe the brightness weight as a parameter that gives a high value to well-exposed pixels and a low value to overexposed grey values. The Resulting LHE V and MSR V channels may be excessively amplified in some pixels, resulting in an odd and distorted picture. One solution to the over-enhanced issue is to apply brightness weights, which guarantee that over-enhanced pixels get less weight values, while well-enhanced pixels receive more. The brightness weight may be written as follows:

Where,
is the no of derived inputs
is the derived input
0.5 is the approximate mean and 0.25 is the approximate standard deviation

Another kind of weight employed in the suggested technique is the Laplacian weight, which is created by applying a Laplacian filter on the three derived inputs. A high Laplacian weight value is connected with features and edges, while a low Laplacian weight value is associated with the other remaining pixels. The Laplacian Weight provides sufficient augmentation at

Journal of Chemical Health Risks
www.jchr.org
JCHR (2024) 14(1), 1183-1196 | ISSN:2251-6727

the borders to make nuclei and surrounding tissue characteristics more identifiable than they were before, and it is determined as follows

Where denotes the Laplacian filter's kernel and denotes the derived input. Then, these two weights are normalised to generate the final weight specified in equation (20), which will be utilised to appropriately blend the three derived inputs.

Where N is the total number of derived inputs and weights determined, which is equal to three. Figure 3 illustrates each of the computed weights. The first column specifies the three V channel inputs: V1, V2-MSR, and V3-LHE. To keep things simple, these inputs are shown in colour. The second column indicates the brightness weight for each computed input, while the third column indicates the Laplacian weights . The final column comprises normalised weights , which are computed from the first two.

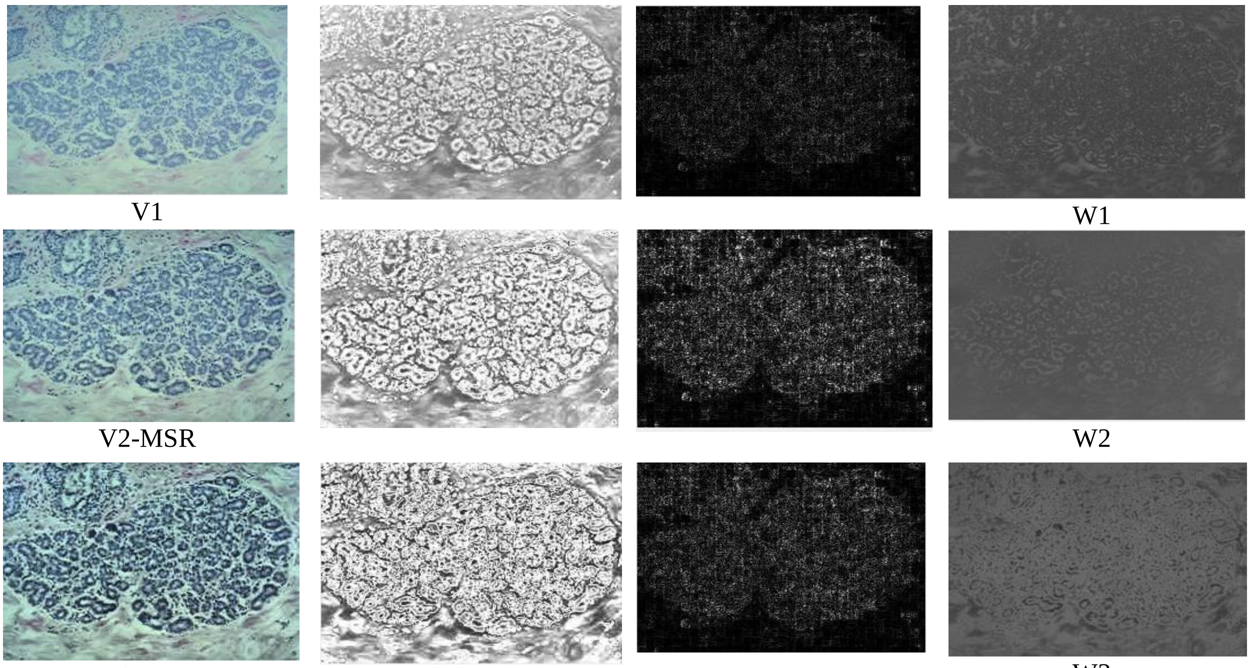


Fig.3 Derived inputs and it's corresponding weights

3.5. Multiscale fusion

The last step is to combine all of the computed inputs using the resulting weights. There are many ways for fusing these inputs and their resultant weights, including naïve fusing and multi-scale filters [27]. These fusion approaches often introduce undesirable artefacts into the final augmented picture and are more computationally intensive. The suggested approach employs a pyramid methodology [28] to provide a more unified result. To begin, each computed input is transformed to a Laplacian pyramid, followed by a Gaussian pyramid for each normalised weight. The Laplacian and Gaussian pyramids both have the same number of levels, which in the suggested technique is set to five. Laplacian and Gaussian operations [29] are both frequently used and straightforward to implement. The product term is produced by multiplying each level of the Gaussian and Laplacian pyramids by the input and weight, and lastly, the output is created by summing all the product results obtained for each input and weight for each level using equation no (30).

Where is the number of inputs, which in this example is three, and denotes the number of levels in pyramids, which equals five. is the Gaussian pyramid of weights, and is the Laplacian pyramid of inputs. The Final V component is created by adding all the outputs at each level and upsampling each output to the preceding one, as specified in equation no. (22) and as shown in the following equation.

The increased V component is then combined with the remaining hue (H) and saturation (S) components to create the final colour histology picture.

Results

This section presents the experimental setup, materials, performance parameters and results.

Journal of Chemical Health Risks
www.jchr.org
JCHR (2024) 14(1), 1183-1196 | ISSN:2251-6727

3.6. Experimental Setup

The experimental setup features are given in Table 2

Table 2 Set up Parameters

SPECIFICATIONS	
Processor	Intel core I5, 8th Gen
Memory	16 GB
Operating System	Windows 10 (64 bit)
Tool used	MATLAB
Version	10
Number of images	10
Images Type	Color image
Width (LHE)	0.001
Window size (LHE)	8*8
Gaussian filter	15, 80, 250
Gaussian filter	1/3

3.7. Material

To compare the proposed approach to established standard image improvement techniques, a range of low-quality digital histopathology photos were chosen from a number of pathology databases, including the UW medical pathology resources, webpathology, and the HAPS histology image collection. These datasets are freely accessible and have been created for educational purposes.

3.8. Performance parameters

The suggested approach is compared to many known contrast enhancement methods for low-quality digital histopathology photos. The outcomes are examined subjectively and objectively. The obtained results were objectively analysed using a variety of evaluation parameters, including the Absolute Mean Brightness Error (AMBE), the Structural Similarity Index Measurement (SSIM), the Feature Similarity Index Measurement (FSIM), the Universal Image Quality Index (UIQI), and the Other Significant Quantitative Measure Peak Signal to Noise Ratio (PSNR).

• **Absolute Mean Brightness Error(AMBE)**

It is used to determine the extent to which the suggested solution preserves brightness, and for optimal performance, AMBE should be as low as feasible. It is determined by subtracting the mean of the greyscale values in the original and suggested images and is denoted by [1].

Where,
m(x) is the average pixel of the input image
M(y) is the average pixel of enhanced image

• **Structural Similarity Index Measurement (SSIM)**

The SSIM is used to quantify the deterioration of structural information in the output processed picture, as well as the structural information disparities between the original and improved images. The following equation [2] is used to compute it.

SSIM values are typically in the range of -1 to 1, and for optimal performance, they should be near to the maximum value, which is one.

Where

are the mean of pixels in the original and output image.
are the standard deviation of the original and output image.
contains the correlation coefficient between input and output image
are the constants

• **Feature Similarity Index Measurement (FSIM)**

Another critical similarity metric is the SSIM, which quantifies the deterioration of feature information in the processed picture and estimates the discrepancies between the input and output images' feature details. The following equation [2] is used to compute it. FSIM values normally lie between -1 and 1, and for best performance, they must be near the highest value of one.

Where
are the rows and columns
is the size of the original image
describes the feature similarity both images
measures the phase congruency []

• **Universal image quality index (UIQI):**

UIQI is one of the most extensively used and significant similarity measures; it is an overall similarity index composed of three similarity measures: contrast, brightness, and structure. It is calculated using the hybrid equation. UIQI values are usually between -1 and 1, and for best performance, they should be close to the maximum value of one.

Journal of Chemical Health Risks

www.jchr.org

JCHR (2024) 14(1), 1183-1196 | ISSN:2251-6727

Where

are the mean intensity of corresponding input and output image

are the standard deviation of the original and output image.

- **Peak Signal to Noise Ratio (PSNR)**

PSNR is another performance metric used to determine the state of improved output. It is derived by dividing the input signal to noise ratio by the processed output signal to noise ratio. It is expressed as a decibel number, and a higher PSNR value suggests a higher-quality picture with less noise. It is said as follows:

Where,

is the of the maximum value of the gray level range of image

is the mean square error between original and output image and it is given as:

Where

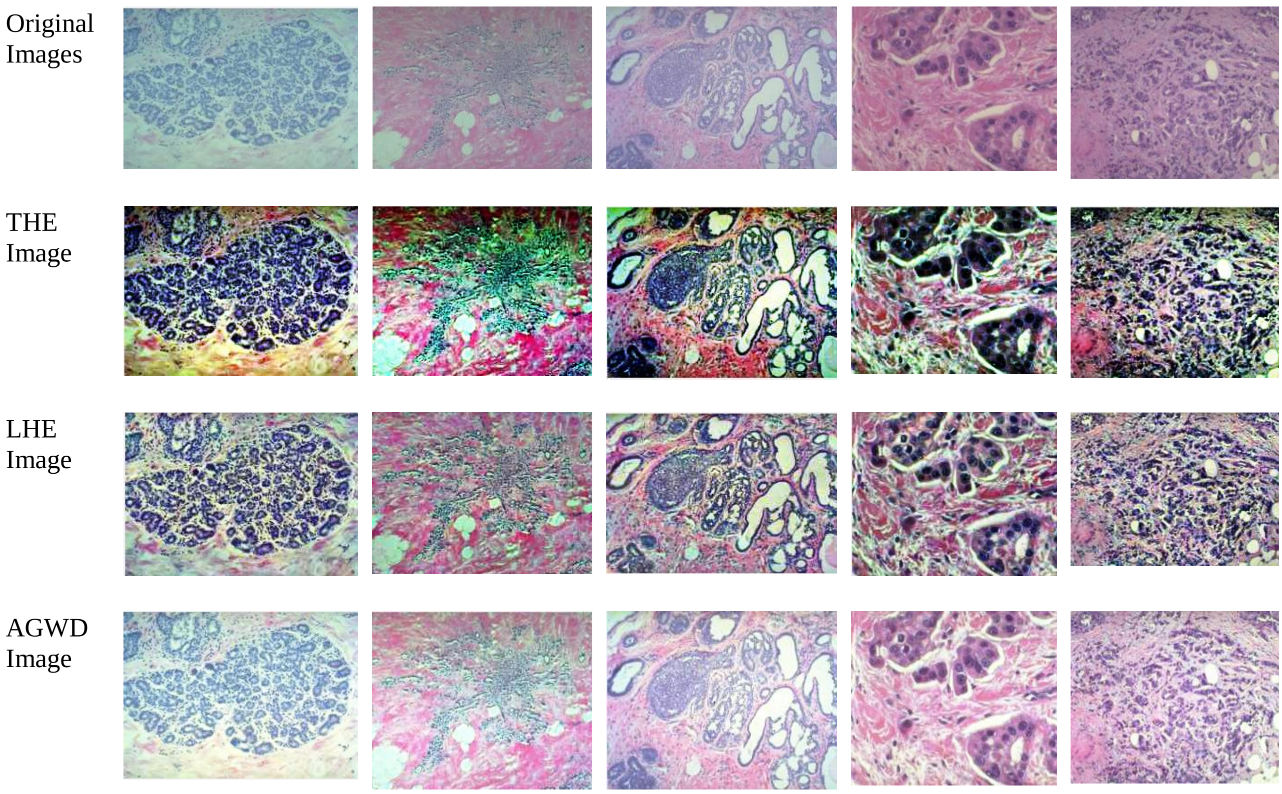
are the rows and columns

are the size of the image

are the input and output image respectively

3.9. Subjective results

This section compares the proposed technique to various current improvement strategies for low-quality digital histopathology photos on a subjective. Subjective assessment entails visual comparison of outcomes, which include output pictures processed using the suggested and other established techniques. Ten low contrast histopathology pictures were chosen for examination. THE, LHE, AGWD, MSR, and DHE are now utilised as standard approaches for comparison. This section discusses the initial low contrast histopathology photos and the improved output obtained by applying various approaches to these input images; five of 10 images are presented in Figure 4. The first row comprises five histopathological photos, the second row provides the results of the first technique THE, the third row contains the results of the LHE method, and so on. The last row corresponds to the picture that has been proposed.



Journal of Chemical Health Risks
www.jchr.org
JCHR (2024) 14(1), 1183-1196 | ISSN:2251-6727

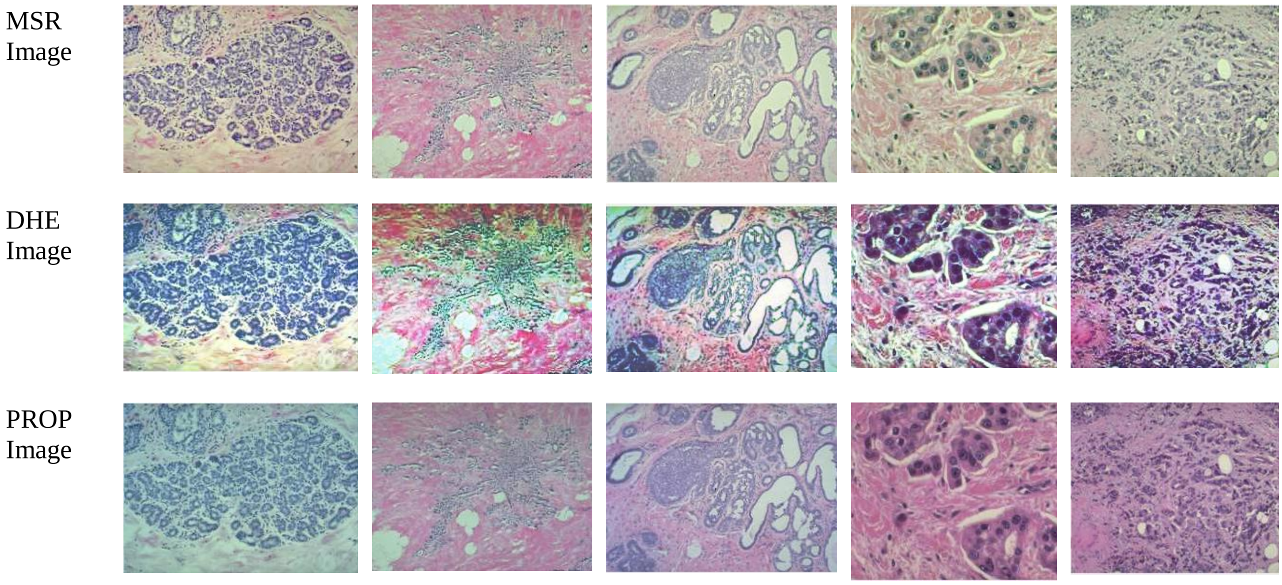


Fig. 4 Visual outputs

3.10. Objective results

This section compares the proposed technique to various current improvement strategies for low-quality digital histopathology photos on an objective basis. The objective evaluation process involves a comparison of findings using a variety of assessment metrics, including AMBE, SSIM, FSIM, UIQI, and PSNR as shown in Figs 5-9. Ten low contrast histopathology pictures were chosen for examination. THE, LHE, AGWD, MSR, and DHE are now utilized as standard approaches for comparison.

4. Discussions

4.1. Subjective discussions

After visual inspection of the findings, it is possible to conclude that THE creates photos with colour distortion, resulting in strange histopathological images. Although LHE generated better photographs than THE, there is a significant difference between the input and output images in terms of brightness, hues, and, most notably, the nucleus blue color is intensified. AGWD produces a pale picture with practically little colour. MSR produces a distorted picture with a yellowish hue, while DHE produces an over-exposed image. The suggested approach generates balanced enhanced histopathology pictures that are neither over- nor under-exaggerated. The nucleus blue hue and surrounding tissue colour have been improved significantly, resulting in a histopathological picture in which each component is clearly differentiated from the others.

4.2. Objective discussions

4.2.1. AMBE performance:

Figure 5 illustrates the performance of numerous enhancement approaches and the suggested strategy in terms of AMBE. Several points should be made.

- It can be shown that AGCW and THE provide the greatest AMBE values across all photos.
- MSR and DHE provide the next greatest mean brightness values, however LHE generates a lower AMBE value than traditional procedures.
- As shown by the average values line graph, the suggested approach has the lowest mean brightness of the others.

Journal of Chemical Health Risks
www.jchr.org
JCHR (2024) 14(1), 1183-1196 | ISSN:2251-6727

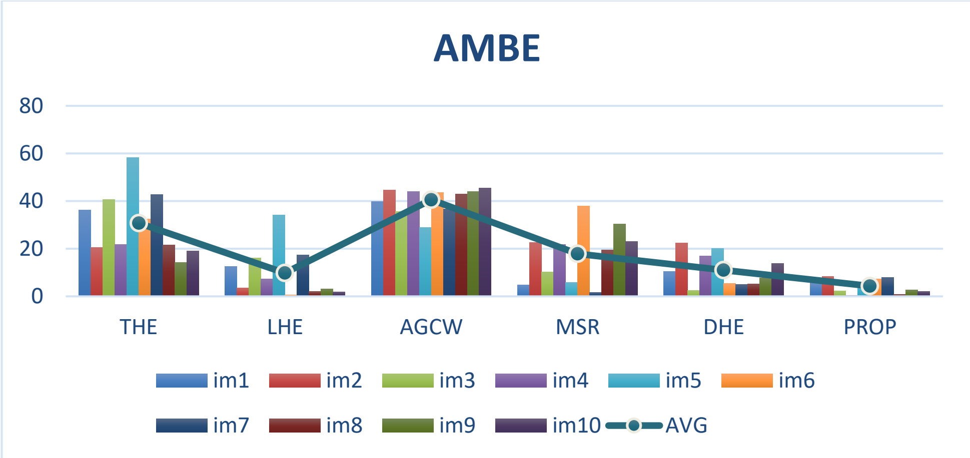


Fig. 5: AMBE chart

4.2.2. FSIM performance:

Figure 6 illustrates the performance of numerous enhancement approaches and the suggested strategy in terms of FSIM. The following information is noted:

- In comparison to previous approaches, the suggested strategy demonstrates the largest value of feature similarity. Additionally, multi-scale retinex (MSR) and adaptive gamma with weighted distribution (AGCW) provide the best FSIM results.
- While dynamic and local improvement approaches perform well on average across all 10 test photos, histogram equalisation gives the lowest FSIM score, indicating that its feature information is largely corrupted.

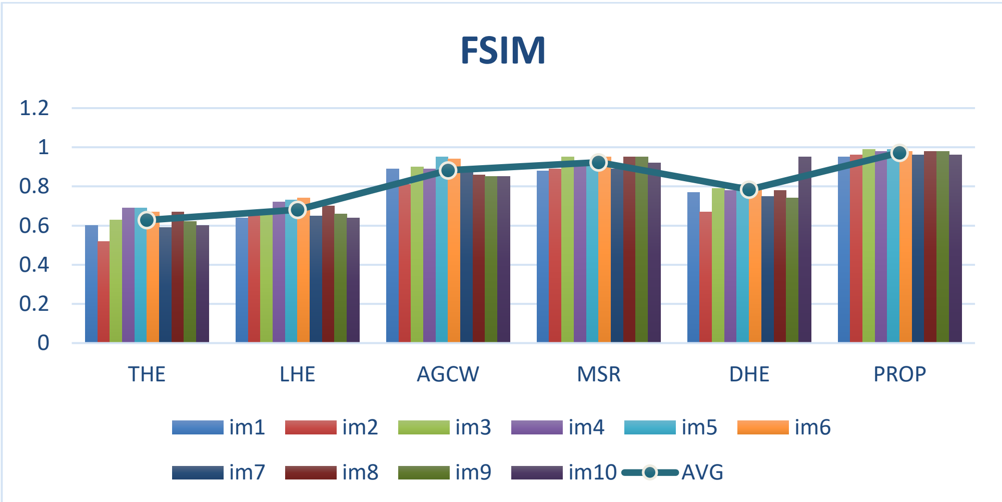


Fig. 6: FSIM chart

4.2.3. SSIM performance:

Along with the mean brightness error and feature similarity index, another matrix is used to determine the efficiency of an output picture. This matrix is termed the structural similarity index (SSIM). Figure 7 shows the SSIM graph. The following data is gathered:

- The suggested approach is capable of preserving structures in improved images and so has a higher value than previous enhancement strategies.
- Compared to other conventional approaches, AGCW and local HE perform better in terms of structural similarity.
- Almost all 10 photos of MSR and dynamic HE had SSIM values between 0.4 and 0.6.
- Traditional Histogram Equalization (THE) has the lowest SSIM value (less than 0.2), indicating that the output HE pictures are more structurally deformed.

Journal of Chemical Health Risks
www.jchr.org
JCHR (2024) 14(1), 1183-1196 | ISSN:2251-6727

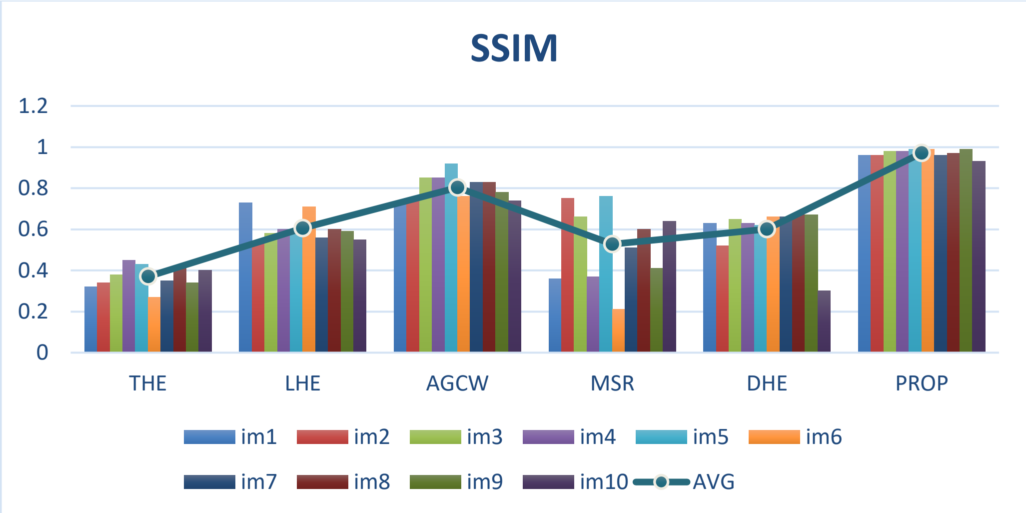


Fig. 7: SSIM chart

4.2.4. UIQI performance

Figure 8 illustrates the effect of the suggested strategy combined with different improvement strategies on UIQI. The following are highlighted points.

- Almost all approaches provide good results in terms of the universal quality index, and the proposed strategy once again outperforms other established ways in terms of UIQI. The proposed approaches exhibit less distortion in terms of structure, brightness, and contrast.
- MSR and AGCW also optimise the findings acquired from all test photos and take a higher value than the other methods.
- The UIQI value is also kept in the case of DHE and LHE, although THE yields the lowest UIQI values, which are almost equal to 0.8.

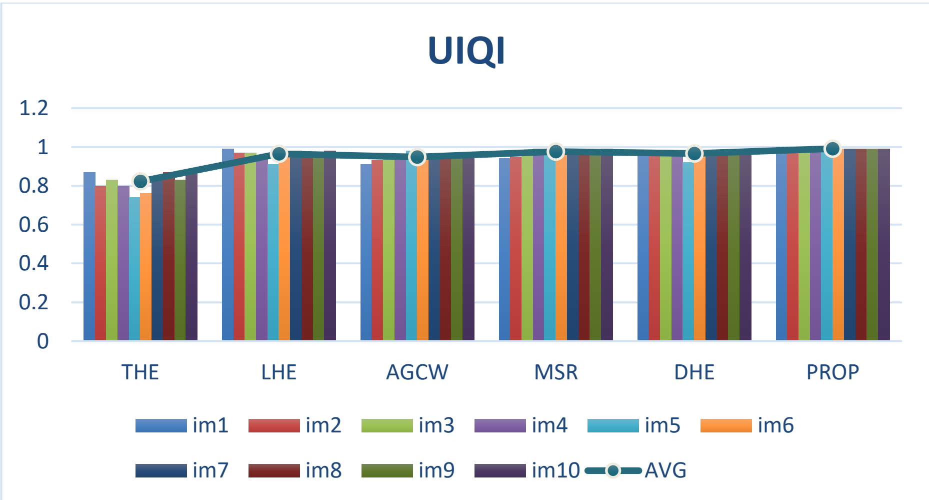


Fig. 8 UIQI chart

4.2.5. PSNR performance

Figure 9 illustrates the effect of planned and varied enhancing approaches on PSNR. The following information is noted:

- The suggested approach displays the greatest signal-to-noise ratio for each of the 10 test photos, with all values falling between 25 and 35. This results in the least amount of distortion and noise in the resulting picture.
- MSR has the second highest PSNR score, which indicates that it is less distorted and noisy. The average PSNR value is presented in the average line graph after the DHE and LHE.
- HE has the lowest PSNR score, which is about 10 for practically all of the ten photos, which is undesirable.

Journal of Chemical Health Risks
www.jchr.org
JCHR (2024) 14(1), 1183-1196 | ISSN:2251-6727

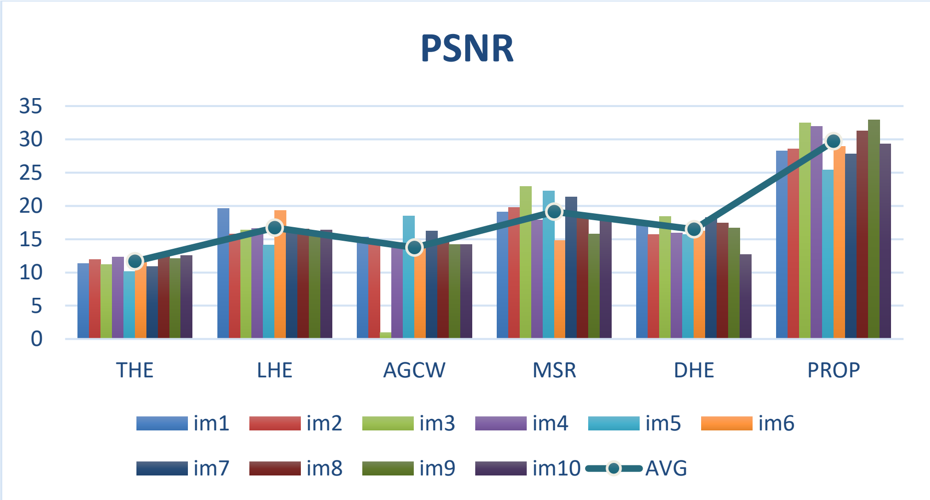


Fig. 9: PSNR chart

5. Conclusion

This article described a strategy for compressing histopathology photos with low contrast using a blended-based improved approach. The proposed scheme addresses issues such as over enhancement, under enhancement, improving contrast, enhancing details, and preserving naturalness by first implementing a luminance measuring method to obtain the brightness channel. Then, by selecting appropriate inputs and weights from the calculated luminance channel, the proposed scheme adequately addresses issues such as over enhancement, under enhancement, improving contrast, enhancing details, and preserving naturalness. The suggested approach is compared to a prominent existing picture enhancement technology in Table 3. From the evaluation of experimental outputs obtained using various enhancement techniques, it can be determined that the suggested strategy has the best control over mean brightness error, while THE and AGCW have the poorest values of AMBE. The suggested scheme's structural similarity index is maximal, as is the AGCW technique. The suggested technique preserves more features, and AGCE, MSR also performs well in the FSIM. Because LHE has a low AMBE value, it also has the lowest SSIM and FSIM values. The suggested technique has a very high universal quality index, and UIQI has also been shown to be the best for LHE, AGCW, and MSR. THE continues to provide unacceptable results when SSIM, FSIM, and UIQI are used. LHE and AGCW produce pictures with a modest amount of noise. The suggested system has the highest signal-to-noise ratio, followed by the MSR, which has the second-best signal-to-noise ratio, whilst THE has the highest noise content. This paper concluded that the suggested strategy produces more attractive outcomes in subjective and objective evaluations than other enhancement strategies currently available in the literature.

Table 3 Overall Conclusion

PARAMETERS	AMBE	SSIM	FSIM	UIQI	PSNR
THE	VERY HIGH	VERY LOW	VERY LOW	MODERATE	VERY LOW
LHE	LOW	LOW	LOW	HIGH	MODERATE
AGCW	VERY HIGH	HIGH	HIGH	HIGH	MODERATE
MSR	MODERATE	MODERATE	HIGH	HIGH	HIGH
DHE	LOW	MODERATE	MODERATE	HIGH	MODERATE
PROPOSED	**VERY LOW**	**VERY HIGH**	**VERY HIGH**	**VERY HIGH**	**VERY HIGH**

Declarations

Funding

No funding was received to assist with the preparation of this manuscript.

Conflicts of interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Availability of data and material

For the comparison of the proposed technique with the existing standard image enhancement techniques, a variety of poor-quality digital histopathology images have been selected from various pathology datasets such as UW medicine pathology resources, webpathology, and HAPS histology image database. These datasets are publicly available and made for educational purposes.

Journal of Chemical Health Risks

www.jchr.org

JCHR (2024) 14(1), 1183-1196 | ISSN:2251-6727

Code availability

Not applicable

References

1. Rubin, R., Strayer, D., Rubin, E., McDonald, J.: Rubin's Pathology: Clinicopathologic Foundations of 21 Medicine. Lippin cott. Williams & Wilkins; 2007.pp. 22
2. Gurcan, M.N., Boucheron, L., Can, A., Madabhushi, A., Rajpoot, N., and Yener, B.: Histopathological 23 Image Analysis: A Review. IEEE Rev Biomed Eng, 2009; 2: 147–171.
3. Gonzalez R.C, Woods R, Digital image processing (Addison-Wesley, Reading, MA, 2nd edn.) 1992, pp 85–103.
4. SM Pizer, RE Johnston, JP Ericksen, BC Yankaskas, KE Muller, Contrast-limited adaptive histogram equalization: speed and effectiveness (Proceedings of the First Conference on Visualization in Biomedical Computing, United States). 1990; 337–345. https://doi.org/10.1109/VBC.1990.109340
5. G.H Golub, and C.F Van Loan. The Hessenberg and Real Schur Forms, Matrix Computations, 3rd ed. Baltimore, MD: Johns Hopkins University Press, 1996; 361-372.
6. Kim Y. T, Contrast enhancement using Brightness Preserving Bi-histogram Equalization. In: IEEE Transactions on Consumer Electronics. 1997; 43(1): 1-8. https://doi.org/10.1109/30.580378
7. Wang Y, Chen Q, and Zhang B, Image Enhancement Based on Equal Area Dualistic Sub- Image Histogram Equalization Method. In: IEEE Transactions on Consumer Electronics. 1999; 45(1): 68-75. https://doi.org/10.1109/30.754419
8. Chen S. D, Ramli A. R. Minimum mean brightness error bi- histogram equalization in contrast enhancement. In: IEEE Transactions on Consumer Electronics. 2003; 49(4): 1310–1319. https://doi.org/10.1109/TCE.2003.1261234
9. Abdullah-Al-Wadud M, Kabir M. H, Dewan M. A. A, (2007) A dynamic histogram equalization for image contrast enhancement. In: IEEE Trans. Consum. Electron 53(2):593–600. https://doi.org/10.1109/TCE.2007.381734
10. Chen S. D, Ramli A. R. Contrast enhancement using Recursive Mean-separate Histogram Equalization for scalable brightness preservation. In: IEEE Transactions on Consumer Electronics, 2003; 49(4) :1301-1309. https://doi.org/ 10.1109/ TCE.2003.1261233
11. Sim K.S, Tso C.P, Tan Y, Recursive sub image histogram equalization applied to gray-scale images. Pattern Recognit.Lett. 2003; 28(10) :1209–1221. https://doi.org/10.1016/j.patrec.2007.02.003
12. Demirel H, Anbarjafari G, Jahromi M.N. Image equalization based on singular value decomposition, in: Proc. 23rd IEEE Int. Symp. Comput. Inf. Sci., Istanbul, Turkey. 2008; 1–5. https://doi.org/10.1109/ISCIS.2008.4717878
13. Demirel H, Ozcinar C, Anbarjafari G. Satellite image contrast enhancement using discrete wavelet transform and singular value decomposition, IEEE Geosci. Remote Sens. Lett. 2010; 7: 333–337. https://doi.org/10.1109/ LGRS.2009.2034873
14. Bhandari A.K, Kumar A, Padhy P.K. Enhancement of low contrast satellite images using discrete cosine transform and singular value decomposition, World Acad. Sci. Eng. Technol. 2011; 55: 35–41. https://doi.org/10.5281/ zenodo.1331359
15. Tan T. L, Sim K. S, Tso C. P, Chong A. K. Computed tomography images by adaptive histogram equalization-application for improved ischemic stroke detection, 2012; 22:153-160. I: https://doi.org/10.1002/ima.22016
16. Huang and Yeh, Image Contrast Enhancement for Preserving Mean Brightness without Losing Image Features, ELSEVIER Engineering Applications of Artificial Intelligence, 2013; 26(5):1487-1492. https://doi.org/10.1016/ j.engappai.2012.11.011
17. Huang S.C, Cheng F.C, Chiu Y.S. Efficient contrast enhancement using adaptive gamma correction with weighting distribution. Image Processing. IEEE Transaction. 2013; 22(3): 1032-1041. https://doi.org/10.1109/ TIP.2012.2226047
18. Atta R, Farouk R, Abdel K. Brightness preserving based on singular value decomposition for image contrast enhancement. 2015; 126: 799-803. https://doi.org/10.1016/j.ijleo.2015.02.025
19. X Fu, J Wang, D Zeng. Remote Sensing Image Enhancement Using Regularized-Histogram Equalization and DCT, IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, 2015; 12(11). https://doi.org/10.1109/ LGRS.2015.2473164
20. N.C.Y. Koh, K.S. Sim. CT Brain Lesion Detection through Combination of Recursive Sub-image Histogram Equalization in Wavelet Domain and Adaptive Gamma Correction with Weighting Distribution, ICORAS. 2016. https://doi.org/10.1109/ICORAS.2016.7872603
21. M Sahnoun, F Kallel, M Dammak. Spinal cord MRI contrast enhancement using adaptive gamma correction for patient with multiple sclerosis, Signal, Image and Video Processing. 2020; 14; 377–385. https://doi.org/10.1007/ s11760-019-01561-x
22. M Sahnoun, F Kallel, M Dammak.. A Modified DWT-SVD Algorithm for T1-w Brain MR Images Contrast Enhancement, IRBM. 2019; 40(4): 235-243. https://doi.org/10.1016/j.irbm.2019.04.007
23. B Subramani, M. Veluchamy. A fast and effective method for enhancement of contrast resolution properties in medical images. Multimedia Tools and

Applications. 2020; 79: 7837-7855. https://doi.org/ 10.1007/s11042-019-08521-0
24. S. Jeevakala, A. Brintha Therese, Sharpening enhancement technique for MR images to enhance the segmentation, Biomed. Signal Process. Control. (2018): 21–30. https://doi.org/10.1016/ j.bspc. 2017.11.007
25. Rao K, Agarwal A, Dhall S (2018) A Novel Hybrid Contrast Enhancement Technique. 3D Research springer 9(3). https://doi.org/10.1007/s13319-018-0178-7
26. Parihar A. S. and Singh K A (2018) study on Retinex based method for image enhancement. in Proc. 2nd Int. Conf. Inventive Syst. Control (ICISC), Coimbatore, India: 619–624. https://doi.org/10.1109/ ICISC.2018.8398874
27. Burt P. J, Adelson E.H (1983) The Laplacian pyramid as a compact image code. In: IEEE Trans. Commun. 31 (4):532–540. https://doi.org/10.1109/ TCOM.1983.1095851
28. Fronthaler H, Kollreider K, Bigun J (2007) Pyramid-based image enhancement of fingerprints. In: IEEE 2007 I.E. Workshop on Automatic Identification Advanced Technologies 45–50. https://doi.org/10.1109/ AUTOID. 2007.380591
29. Liu X, Tang J, Xiong S, Feng Z, Wang Z (2009) A multiscale contrast enhancement algorithm for breast cancer detection using Laplacian Pyramid. In: IEEE International Conference on Information and Automation, ICIA'09 :1167–1171. https://doi.org/ 10.1109/ICINFA.2009.5205093
30. Parihar A. S. and Singh K A (2018) study on Retinex based method for image enhancement. in Proc. 2nd Int. Conf. Inventive Syst. Control (ICISC), Coimbatore, India: 619–624. https://doi.org/10.1109/ ICISC.2018.8398874
31. Kumar, S., Bhandari, A.K., Raj, A., Swaraj, K., Kumar, S.: Triple Clipped Histogram Based Medical Image Enhancement Using Spatial Frequency. IEEE Transactions on Nano Bioscience, (March 2021)
32. Kumar, U., Kumar, A,S.: Genetic algorithm based adaptive histogram equalization (GAAHE) technique for medical image enhancement. Optik, 230 (March 2021)
33. Rao, K., Bansal, M. & Kaur, G.: An optimized morphology transform-based diagnostic computed tomography image enhancement using edge map. International Journal of Imaging Systems and Technology (2022).