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Original Article

Performance Comparison of Image Processing-Based Contrast Enhancement Algorithms on Microscopic Longitudinal Muga Silk Images

Pinki Devi[1], Mirzanur Rahman[2] , Dankan Gowda V[3], Uzzal Sharma[4], Manjunath R.N[5]

[1,2]Department of Information Technology, Gauhati University, Guwahati, India.
[3]Department of Electronics and Communication Engineering, B.M.S Institute of Technology and Management, Bangalore, India.
[4]Department of Computer Science, Birangana Sati Sadhani Rajyik Vishwavidyalaya, Golaghat, India.
[5]Central Muga Eri Research and Training Institute (CMER&TI), Jorhat, Assam. India.

[2]Corresponding Author : mr@gauhati.ac.in

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Abstract *- The "Queen of Textiles" alludes to silk, which is known for its high-quality fabric. Assam contributes for 95% of the country's Muga silk production. The term silk originates from a type of worm commonly known as the silkworm. Sericulture is the technique of raising silkworms to produce silk. The purity of silk can be tested using traditional methods; in the present era, we are contemplating digital techniques. In recent years, image processing techniques have been coupled with Artificial Intelligence, Machine Learning, and Deep Learning to make the purity assessment procedure even easier. To evaluate purity, a good-quality image is needed. We can improve image quality by using image processing and computer vision algorithms. Muga silk has its own exquisite qualities and complex textures; silk images often face unique challenges when it comes to contrast enhancement. It has additional hurdles when categorizing different types of silk due to image quality. In this study, we compare two image contrast enhancement approaches on a small dataset of specially recorded microscopic longitudinal Muga silk photographs. The current work employs image contrast enhancement approaches such as Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE). The goal of this research is to find the best strategies for increasing contrast while preserving the delicate features and distinctive attributes of microscopic longitudinal Muga silk weaves. Our experimental results show that CLAHE is a good strategy for improving the visual quality of microscopic longitudinal Muga silk images.*

Keywords *-* *Muga Silk, Antheraea assamensis, Contrast enhancement, Histogram Equalization(HE), Contrast Limited Adaptive Histogram Equalization(CLAHE), Microscopic image, longitudinal view.*

1. Introduction

Contrast is an important feature of an image. It is a powerful component of an image since contrast has its own properties. Contrast is the difference in brightness between the lightest and darkest parts of an image. Contrast is an important parameter because we may need to increase or decrease the brightness of an image. In some cases, we need to increase or decrease the brightness of an image. Using contrast enhancement, we can get to know the hidden properties of an image. According to previous studies, we can conclude that for different categories of images need to use different enhancement techniques to get the desired results. Image enhancement is a major part of an image, which includes all the minor factors of an image, like Contrast Enhancement, Spatial Filtering, Density Slicing, and FCC. Using image enhancement techniques, we can easily identify all the important factors of an image. Nowadays, there are various types of image enhancement techniques as well as contrast enhancement techniques available. Contrast enhancements increase the brightness difference between items and their backgrounds and make each object more readable by humans as well as by computers. To reduce the noise in the image, we can use a pre-processing technique so that the noise can be reduced from the image.

Some techniques of image enhancement, which are a very important factor of an image, especially, are concentrated on spatial domain techniques [1]. This includes HE, BBHE, CLAHE, and RMSHE. Image thresholding and log transformation have been studied extensively for contrast enhancement in images [2-4]. RMSHE is a similar technique to the Histogram equalization method whenever no sub-image is generated. Additionally, the proposed phase information-based contrast enhancement framework introduces a novel approach by transforming phase changes into magnitude variations to enhance structural details and improve visibility in microscopy images, outperforming existing enhancement techniques [5]. The histogram equalization is used in every field to enhance the contrast of an image. It is a traditional contrast enhancement technique. In speech recognition, medical image processing, and many more applications, HE is used [6, 7]. Histogram Equalization has some disadvantages, which are explained in some research [8]. Many researchers researched image and video contrast enhancement [9, 10]. A new approach has been developed, which is Brightness Preserving Weight Clustering Histogram Equalization (BPWCHE) [11]. This approach mainly focuses on decreasing the preparation time and building an effective method for the speedy improvement of the contrast of an image. An improved version of histogram equalization is also discussed in [12], which is named Bi Histogram Equalization. The Bi HE method tries to overcome the brightness preservation problem and preserve the needful brightness. An adaptation of Histogram equalization, termed CLAHE, is proposed by [13,14]. In CLAHE, it works in a different manner. Firstly, it divides the input image into several blocks and then applies CLAHE in every block separately to enhance the contrast of the image. Furthermore, the synthesis of Muga silk nanoparticles using the microwave-assisted radiolysis method showcases the evolution of secondary structures and the characterization of these nanoparticles for potential wide applications, emphasizing the significance of understanding their properties for feature advancements [15].

Some algorithms increase the contrast of the images, but sometimes they give some undesirable results, so that these approaches are not feasible for microscopic Muga silk images. Whenever we try to keep silk images in a digital format, capturing their essence in images can sometimes prove challenging due to variations in lighting, texture, and color.

Muga silk, known as the "Golden Silk of Assam," is renowned for its natural golden sheen and durability and is one of the most prized silk varieties globally. It is produced primarily in Assam, India, from the semi-domesticated Antheraea assamensis silkworm and has been woven into the cultural fabric of the state since ancient times. This silk variety holds unique geographical significance, thriving in the specific climatic conditions of the Brahmaputra Valley, which also extends to Meghalaya and neighboring states [16]. It is believed that Muga silk gained prominence during the Ahom Dynasty (1228–1828), when the Ahom rulers provided significant patronage to its rearers and weavers, helping them refine their skills and prosper. The Ahom kings viewed Muga silk as a royal fabric, storing it for diplomatic gifts and royal use. Under Ahom rule, weaving Muga silk became a thriving household profession, marking a major socio-economic development in Assam. Economically, Muga silk is a vital contributor to the livelihoods of thousands of rural families, significantly bolstering the regional economy through both domestic and export markets.

Today, Muga silk, celebrated for its natural golden luster and remarkable durability, is among the most esteemed silk varieties worldwide. The silk is deeply intertwined with the cultural heritage of Assam, prominently featured in traditional attire such as the Mekhela Chador and ceremonial garments [17]. The exclusivity of Muga silk, coupled with its cultural integration in the weaving process, establishes it as a luxury textile and enhances its economic value. However, despite its rich cultural and economic importance, the trading practices for Muga silk are poorly organized at both national and international levels due to the absence of a well-defined grading system or quality standards specifically tailored for Muga silk yarn. Currently, the quality of Muga silk is assessed based on traditional knowledge, lacking formalized standards for quality evaluation [18]. This deficiency creates numerous challenges for producers and consumers alike, leading to inconsistencies in quality and inequities in trade. In the competitive textile market, the ability to reliably test and grade raw silk is crucial for determining its suitability for various applications and for ensuring that producers receive fair compensation for their efforts.

Muga silk is a highly valued silk variety, with the market price for one kilogram ranging between INR 25,000 and 30,000 in local markets. This premium pricing often attracts unethical practices, such as the selling of counterfeit or adulterated Muga silk. Duplicity usually occurs through the mixing of other silk varieties, such as tasar silk, either during the yarn formation stage or in the weaving process. Tasar silk, in particular, is a commonly used substitute due to its similar physical and chemical properties to Muga silk. Both Muga and tasar silk share a similar component structure, making them almost indistinguishable to the naked eye. The subtle differences between them can only be detected through detailed chemical analysis. However, this type of testing can be both time-consuming and expensive, limiting its practical application for routine quality control. The presence of counterfeit materials in the market not only compromises the authenticity of Muga silk but also affects the credibility of genuine producers and the value of the product. Therefore, it is crucial to establish effective measures for preventing such fraudulent practices. This could include developing simpler, cost-effective testing methods, implementing robust certification processes, and raising awareness among buyers about the characteristics of authentic Muga silk. Ensuring the integrity of Muga silk products will help maintain its premium status and protect the interests of both producers and consumers. Reviewing the current literature on Muga silk and contrast enhancement methods indicates that there have been major difficulties in improving the image of microscopic silk fibers, especially when they belong to the Muga silk, which has special and complex structures. Even though the usage of different image processing methods, including Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE), in general imaging has been investigated on overall contrast improvement, little work has been done on Muga silk images specifically. This gap becomes especially obvious when it comes to the delicate nature of silk fibers, when, in a bid to bring out finer details and increase contrast, it is in question. Thus, the proposed research will address the gap in understanding the efficiency of the HE and CLAHE in enhancing the contrast and visual quality of the microscopic longitudinal Muga silk images, where preserving the original characteristics of this fabric is the primary focus.

2. Literature Review

Queen of Textiles-Muga silk is a luxury fabric that comes in gold color and has a great lasting quality. It is mostly made in Assam, India, and it adds to the Muga silk production in the country. The process of production includes rearing silkworms, which are fed on certain plants, especially some trees, and the silk produced by these silkworms is considered to be of excellent quality. Although Muga silk is greatly valued for its natural shine and feel, it is sometimes difficult to assess its quality. Conventionally, silk purity testing has been performed manually by physical testing and by using the naked eye, and this method may be subjective and is labor-intensive. With the emergence of digital technology, however, newer approaches involving image processing algorithms have started to be of importance in enhancing the quality measurement of Muga silk [19]. The result of these digital methods is high-quality images, which can be evaluated concerning purity and texture, and offer a more objective and more efficient method of evaluation.

Microscopic imaging is also important in the study of Muga silk since the texture and fineness of the silk fibers cannot be seen with the naked eye. It is possible to analyze the surface of the silk with the help of high-resolution microscopic pictures, which helps to detect impurities and estimate the quality of the material. This has been commonly done with the traditional light microscopy, which frequently is not able to produce clear images, particularly with very fine textures, and in cases of varying light conditions. In order to surmount such complications, more developed imaging tools such as Scanning Electron Microscopy (SEM) have been used to obtain finer detail images of the silk fibers and to capture the actual finer details as well. Notwithstanding this development, there are still typical problems with microscopic images of silk due to low contrast and poor lighting that result in the inability to distinguish fine features or detect possible defects. All these problems reveal the necessity to develop effective image processing methods that could be used to improve the quality of images and increase the accuracy of analysis [20].

Image processing has been successfully applied in the silk industry, which has received massive growth with the advancement of digital techniques. There was initially only some rudimentary image processing tools, such as filtering and thresholding; however, there has been a significant increase in the scope of image processing with the invention and advancement of more sophisticated techniques, including Artificial Intelligence (AI) and machine learning. Contrast enhancement is one of the most significant features of image processing in the example of Muga silk. The problem with silk images, especially those made under a microscope, is that they are of low contrast, and it is rather hard to see details and the texture of a finer quality. The purpose of contrast enhancement techniques is to enhance the appearance of these details by altering the level of intensity of the image [21]. This is essential in safeguarding that the delicate peculiarities of the silk are maintained and in making the image more fit to analyze.

One of the most widely deployed contrast enhancement methods is the Histogram Equalization (HE) method, and another is the Contrast Limited Adaptive Histogram Equalization (CLAHE). The All histogram Equalization is a simple technique that reallocates the intensity levels of an image, and this makes the distribution of pixel intensity levels more equal. The effect of this important technique is the enhancement of the total contrast of the image, and it is needed particularly with images whose intensity values are not distributed well. Nevertheless, HE can also be effective to give the global contrast to an image, although most of the time, this is achieved by adding an artifact or over-enhancing some of the regions of the image, and this can result in loss of fine details. It is especially problematic when dealing with complex textures, such as those using Muga silk, where it is important to preserve the natural appearance of the image [22]. Enhancement of contrast is critical in the understanding of details in the low-contrast images. The most used method is called Histogram Equalization (HE), which, at times, causes the fine details to be lost, particularly on the complex textured images such as silk. In order to overcome this, the Contrast Limited Adaptive Histogram Equalization (CLAHE) was proposed, which uses local adaptive equalization so as to avoid detail enhancement in finer details and enhance noise amplification in contrast. Application of CLAHE has been successfully done in medical imaging and microscopy fields, whereby it has been shown to be effective in making images clearer. Reliable, relevant textile imaging. In the context of textiles, conventional ways of evaluating silk quality can be based on either manual inspection or simple imaging procedures, but they fail to deal with the issues of the detailed textures of silk. Muga silk has its peculiar patterns and fine details, which also demand special contrast enhancement to make the images better without any form of distortion on these detailed features. Although progress has been made in general textile imaging, research has not been done specifically on the improvement of Muga silk images. The aim of the paper is to fill this gap by benchmarking the performance of HE and CLAHE on contrasting microscopic longitudinal Muga silk images with emphasis on retaining the intricate characteristics.

To overcome the shortcomings of HE, Contrast-limited Adaptive Histogram Equalization, also known as CLAHE, was created. In comparison to HE, CLAHE operates on the concept of dividing the image into smaller regions or tiles and applying histogram equalization on each region separately. This localized method enables improved control of contrast enhancement in a better localized contrast to ensure the local contrast is improved without excessive enhancement on a particular portion. CLAHE especially works best with microscopic images, in which it is important to maintain each of the tiny details and textures of the fibers of the silk. Through local application of contrast enhancement, CLAHE can retain the natural properties of the silk, as well as enhance the overall image quality. This renders the CLAHE an exceptionally suitable option over sharpening the contrast of microscopic Muga silk images since, in such a context, the enhancement of the quality of the image alongside the conservation of detail is imminent.

The implication of AI and machine learning on image processing processes is also beginning to attract considerable focus in recent years. It has been applied to image enhancement and image classification models trained through AI techniques, specifically, deep learning algorithms such as Convolutional Neural Networks (CNNs). When applied to Muga silk, AI may be employed to analyze microscopic pictures automatically to improve the contrast and determine the most important properties of the silk, i.e., the presence of any impurities or an irregular texture distribution. These models are trainable with a big set of silk images, whereby a system can train to learn to enhance the quality of images without destroying the integrity of features in the silk. The combination of AI and image processing algorithms can make the process of evaluating the silk quality more reliable and quicker, as it can be automated. Histogram Equalization and CLAHE have been compared with each other, and interest has been shown in their application in different image processing tasks. Although both methods are applied in order to bring out contrast, they vary in their performance depending on the intended use and the nature of the pictures undergoing their application. HE tends to be a quicker and simpler technique, although it is not necessarily appropriate for more complex images with intricate textures, such as Muga silk, because it does not take into consideration any local variations of the image. On the other hand, CLAHE is more appropriate for an image that needs finer details, and it achieves processing by increasing the local contrast without producing an over-enhanced image over the whole image. In microscopic images of Muga silk, where the fine details and textures of the fibers should be preserved, CLAHE has proven to be a better process for enhancing the contrast. This research is rather novel as it dwells upon such an exceptionally unique type of fabric as Muga silk, having very rich textures that have never been researched in the framework of contrast enhancement tools. Although past studies have implemented the Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) in order to achieve better image quality on different types of materials, no study has been done to enhance the contrast of microscopic longitudinal images of Muga silk. This paper will compare the results of HE and CLAHE on Muga silk in alleviating the problem of image contrast enhancement without losing thin fibers and unique textures of the piece of cloth. In contrast to the literature, our study is specifically aimed at the conservation of these complex characteristics in silk fibers, offering a more specific solution to the proper evaluation of the quality of Mugha silk.

Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) are the known approaches to contrast enhancement, which were extensively used to enhance the image quality in numerous areas. Nevertheless, the methods are usually restricted when used on complex pictures like the microscopic silk pictures, where fineness is of central importance. Conventional techniques such as HE can increase the contrast of the world, but the textures are erased as well, and this is a negative aspect of the Muga silk material, as it has ornate designs. In addition, CLAHE offers finer detail improvement; it is not widely tested on Muga silk, especially when aiming at preparing microscopic longitudinal pictures. The peculiarities of maintaining the fine and elegant properties of Muga silk and amplifying contrastiveness have not been sufficiently tackled in the earlier studies. This paper will attempt to address this gap by comparing HE and CLAHE on the particular imaging of Muga silk with a view to enhancing the contrast without damaging the integrity of the fabric, which has complex features. Addressing this particular problem, our work contributes to the research on textile image processing in a new way.

3. Morphology of the Muga Silkworm Cocoon

Silk is formed from liquid secretions produced by two large glands located in the posterior region of the silkworm. These secretions are released through a single exit point on the silkworm's head, known as the spinneret. A second set of glands produces sericin, a gummy substance that binds the twin filaments together. Once exposed to air, both secretions harden, creating two tightly bound filaments. As the silkworm spins its cocoon, it rotates its body in a continuous figure motion, steadily constructing the cocoon wall around itself. The outermost layer of the cocoon, known as floss silk, consists of loosely connected fibers with an irregular texture, as shown in Figure 1. below.

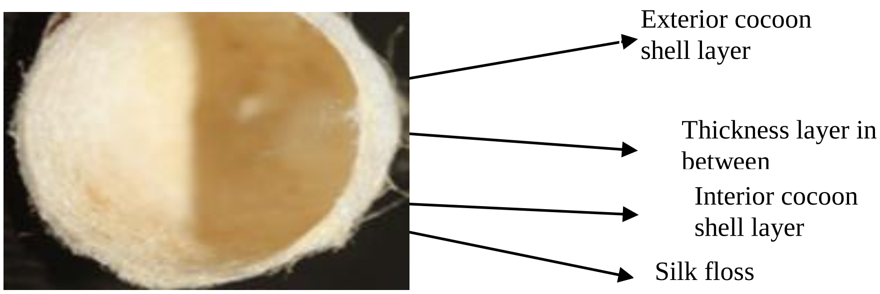


Fig. 1 Cross-sectional view of cocoon construction

The SEM images that illustrate the structural architecture of the cocoon's outer and inner layers, as well as a side view showing the through-thickness layers of the cocoon shell. Each layer of the cocoon is made up of silk fibers, consisting of fibroin, sericin, and microscopic crystals. SEM imaging reveals the morphology of the fibers, which consist of two branches with a flattened cross-section, encased in a layer of sericin. The outermost layers of the cocoon are characterized by low packing density and large gaps between the fibers. However, as one moves from the outermost to the innermost layers, the fiber density increases.

While sericin serves as the bonding agent throughout the cocoon, SEM analysis reveals that it only partially binds the fibers in the outermost layers. In contrast, the fibers in the innermost layers are thoroughly coated in sericin, forming a highly interconnected and strongly bonded network.SEM also reveals the presence of cubic crystals, ranging in size from 0.5 to 2 μm, on the cocoon's outer surface. These crystals decrease in concentration as one moves toward the innermost layers. SEM images of cocoon layers are presented in Figure 2.

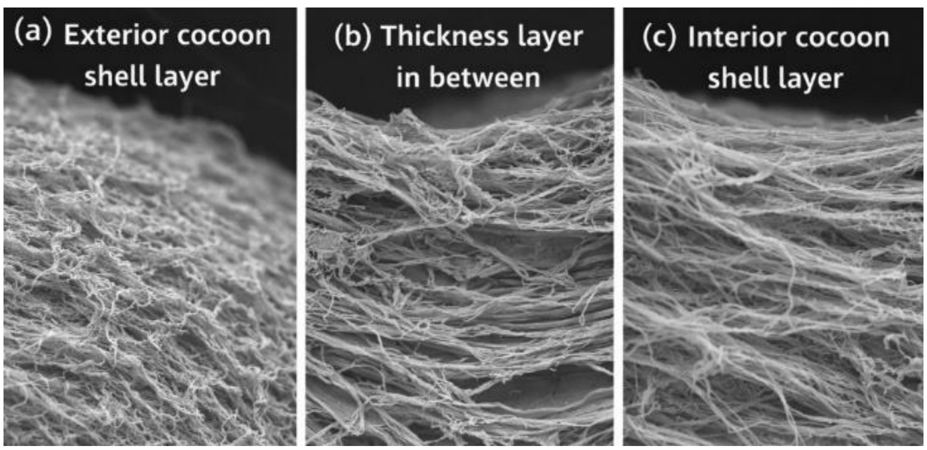


Fig. 2 SEM images of cocoon layers

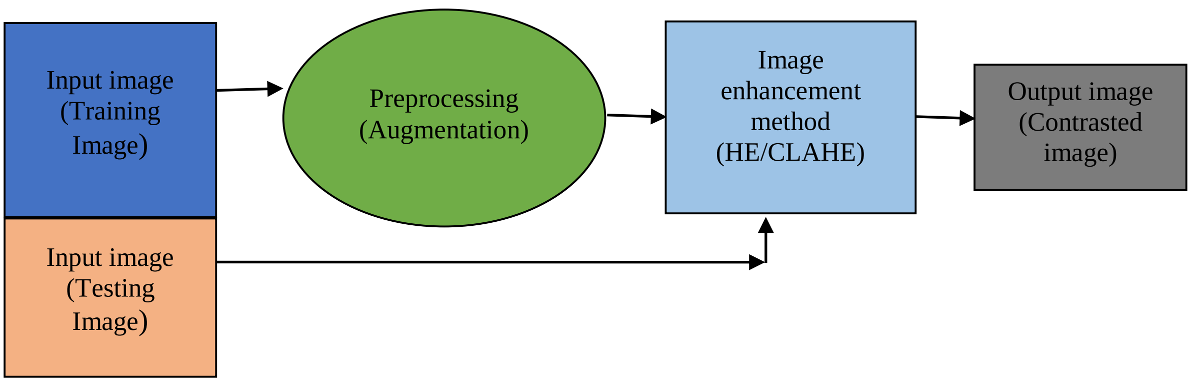


Fig. 3 Flowchart of contrast enhancement methods on microscopic longitudinal muga silk images

4. Proposed Method

The flowchart of the contrast enhancement techniques used on microscopic longitudinal images of Muga silk is given in Figure 3. Here, the process starts with an input image, which may be either a training image or a testing image. The training picture is then processed (preprocessing), which normally involves augmentation processes to increase the variety and quality of data.

The image currently goes through an image enhancement algorithm, either Histogram Equalization (HE) or Contrast Limited Adaptive Histogram Equalization (CLAHE), both of which seek to enhance the image contrast. The last step is the creation of the output image, which is the image that has been improved or contrasted and reflects the results of the improvement, achieved by such enhancement methods.

4.1. Image Acquisition

Digital images are of two types in the context of photography:

4.1.1. Black and White Image

The black and white colors are made of different gray shades, which range from 0 to 255. Here, 0 refers to black and 255 refers to white.

4.1.2. Color Image

RGB stands for Red, Green, and Blue. With the help of these three basic colors, we can make all existing colors according to our needs. Some secondary color models, such as cyan, magenta, and yellow, are formed from two basic colors. In [20, 21], they have discussed various image acquisition techniques.

4.2. Image Dataset

Since we are in the very preliminary stage of our research, the availability of data is a real challenge. So, at this moment, we are starting with a small amount of data. The dataset contains 1000 microscopic Muga silk images. All images are in greyscale and in PNG format. The view of the microscopic images is longitudinal. Since our data are microscopic images, it is very challenging. This image data set is provided by Central Muga Eri Research and Training Institute (CMER&TI), Jorhat, Assam. Microscopic longitudinal images of Muga silk are shown in Figure 4. The close-up shots are taken at one of the highest magnifications to show the fine structure and complexity of the silk fibers. The photos demonstrate the peculiarities of Muga silk, its smoothness, luster, and the sophisticated structure of fibers. The different concentrations of details in the pictures are crucial to realize the quality of the material that is important in studying its purity and classification.

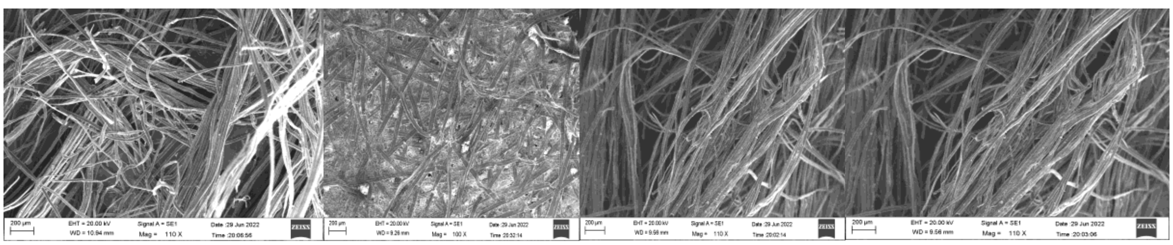


Fig. 4 Images of microscopic longitudinal Muga silk images

4.3. Image Augmentation

It is a technique used in image processing. It is used for various purposes such as geometric transformations, color space *augmentation*, kernel filtering, mixing *images*, random erasing, etc. It can also be used to increase the dataset size. In our case, we are using data augmentation for this purpose only. We are making the dataset larger by resizing, rescaling, random flipping, reshaping, rotating etc to the existing images.

When we do not have a larger number of datasets, we can use image augmentation. In our study, since we do not have a large dataset, we are applying augmentation to make our dataset larger. To mathematically represent the process of image augmentation for increasing the dataset size, we can express it as follows:

Given an original dataset D containing N images, the augmented dataset D′ can be defined as:

$$D' = \{f1(I1), f2(I1), \ldots, fk(I1), f1(I2), f2(I2), \ldots, fk(I2), \ldots, f1(IN), f2(IN), \ldots, fk(IN)\}$$

Where:

- D is the original dataset of N images, I_i (where i=1,2,…, N).
- D' is the new augmented dataset.
- $f_j(I_i)$ represents the *j*-th augmentation function applied to image I_i.
- *k* is the number of different augmentation transformations applied to each image.

By applying multiple transformations to each image in the dataset, the size of the new dataset D' can be significantly larger than *D*, effectively increasing the training data available for model training. As far as the contrast enhancement technique is concerned, we are applying two techniques, namely the spatial domain and the frequency domain. Spatial domain techniques are more popular compared to the frequency domain.

4.4. Spatial Domain

This process mainly aims at the manipulation of pixels in an image. The intensity of pixels of the input images is manipulated to generate the required output. This can be performed using various spatial domain methods, including logarithmic transforms, power law transforms, and histogram equalization, all of which act on the pixels in the picture itself. It is possible to divide these approaches into two categories, which are Spatial Filter Operations and Point Processing Operations. The spatial domain method is especially handy when it comes to changing the gray levels and the contrast of the whole image. In the process, one or more features of the picture can be altered, which may lead to peculiar or unpredictable results on some occasions. Spatial domain techniques can also be classified into two categories: local image enhancement and global image enhancement. Whereas local image enhancement techniques are necessary for the enhancement of the quality of pictures in certain parts of the picture, global image enhancement techniques play a less important role, with global image enhancements being made. Figure 5 shows how a histogram equalization is carried out on a microscopic longitudinal image of the Muga silk. The original image of the Muga silk is presented in panel (a) with the natural texture and contrast. The same image has been given as the Histogram equalized (Panel (b)) version, where the contrast has been added to ensure that details at the small scales of the silk fibers can be seen. The contrast adjustment allows distinguishing fine details that might otherwise have been low in the original image. The Histogram of the equalized image in panel (c) indicates the distribution of pixel numbers after the enhancement of contrast. The Histogram illustrates the redistribution of the pixel values as a result of the equalization process and how the overall contrast of the image becomes more consistent, and the microscopic silk image appears clearer. Figure 6 shows the use of Contrast Limited Adaptive Histogram Equalization (CLAHE) on a microscopic longitudinal Muga silk picture. The original picture of the Muga silk shown in panel (a) is in its natural form and contrast. After the application of CLAHE, the result of panel (b) has been achieved with contrast locally increased to make fine details of silk fibers visible and to avoid over-enhancement in some areas. In panel (c), the Histogram of the enhanced image of panel (b) in terms of CLAHE is made, and the distribution of pixel intensities following the enhancement of contrast is represented. The Histogram reveals the contrast local control of the CLAHE, and the intensities have been more controlled and balanced, rather than in the original image.

4.5. Histogram equalization (HE)

Image enhancement is a process where a set of operations is performed on the input image to improve its visual appearance. Histogram equalization is a basic type of contrast enhancement technique where the overall image contrast is changed with some internal functions or in a part of an image. It is mainly used to boost the global contrast of an image to make it more visible to humans as well as machines. In order to carry out Histogram Equalization (HE), two probability functions are employed by the HE, namely the Probability density function and the cumulative distribution function. Calculated by the Probability density function is,

$$P(Xk) = \frac{n^k}{n} \tag{1}$$

Where, $k = 0,1,2 \ldots\ldots (L-1)$
n^k = Number of times different pixels appear.
n= Total number of pixels.
X_k = No. of pixels that have a specific intensity.
Based on the PDF, one cumulative function is used-

$$C(X) = \sum_{j=0}^{k} P(X_j \;) \tag{2},$$

Where, $X = Xk$

$$K = 0,1,2 \ldots\ldots\ldots (L-1)$$

After this, the histogram equalization appropriates the grey level ($S_{k)}$ and assigns it to the grey level (X_k).

$$Sk\; = (L-1) * C(X) \tag{3}$$

Lastly, HE will round off the (iii) values -

$$\Delta S_k \; = (L-1) * C(X) \tag{4}$$

It is well known that the appearance of the resulting image from the equalization process is not visually good for most cases.

4.6. Contrast-Limited Adaptive Histogram Equalization (CLAHE)

This technique is widely used. This technique is used in a very small area rather than the whole image. CLAHE addresses some of the shortcomings of traditional equalization by limiting the amplification of contrast in local regions of an image. CLAHE divides the entire image into smaller pieces, which are called ‘tiles’, and applies histogram equalization independently to each tile. By constraining the contrast enhancement locally, CLAHE ensures that noise and artifacts are less pronounced while still improving the overall contrast of the image.

$$\mathrm{H_T(i)} \;=\; \sum_{(x,y)\in T} \delta(\mathrm{I(x,y)} - \mathrm{i})$$

Where, H_T(i) is the Histogram of each individual tile, I(x,y) represents the pixel intensity at coordinates (x,y).

$$\mathrm{H'_T\,(i)} = \begin{cases} \mathrm{H_T(i)} & \text{if } \mathrm{H_T(i)} <= L \\ \mathrm{L} & \text{if } \mathrm{H_T(i)} > L \end{cases}$$

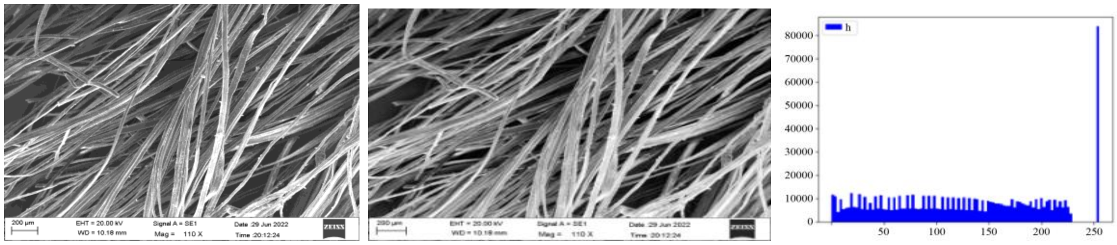
$\mathrm{H'_T}$ (i) is the clip limit of the Histogram.

$$CDFT\;(i) \;=\; \sum_{j=0}^{i} H''_T\,(j)$$

$CDFT\;(i)$ Compute the CDF of the adjusted Histogram.

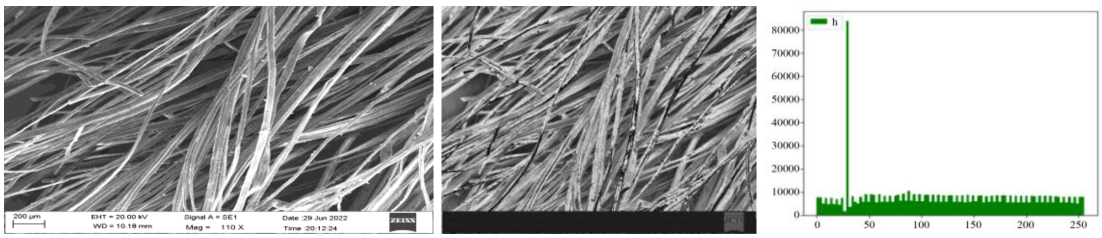
$$O\;(x,y) \;=\; floor(CDFT(I(x,y)) * Max\_intensity)$$

, Where O(x,y) is the mapped image.



(a) (b) (c)

Fig. 5 (a) Original image, (b) Histogram equalized image, and (c) Histogram of (b).



(a) (b) (c)

Fig. 6 (a) Original image, (b) CLAHE image, and 1(c) Histogram of (b).

ORIGINAL IMAGE HE CLAHE

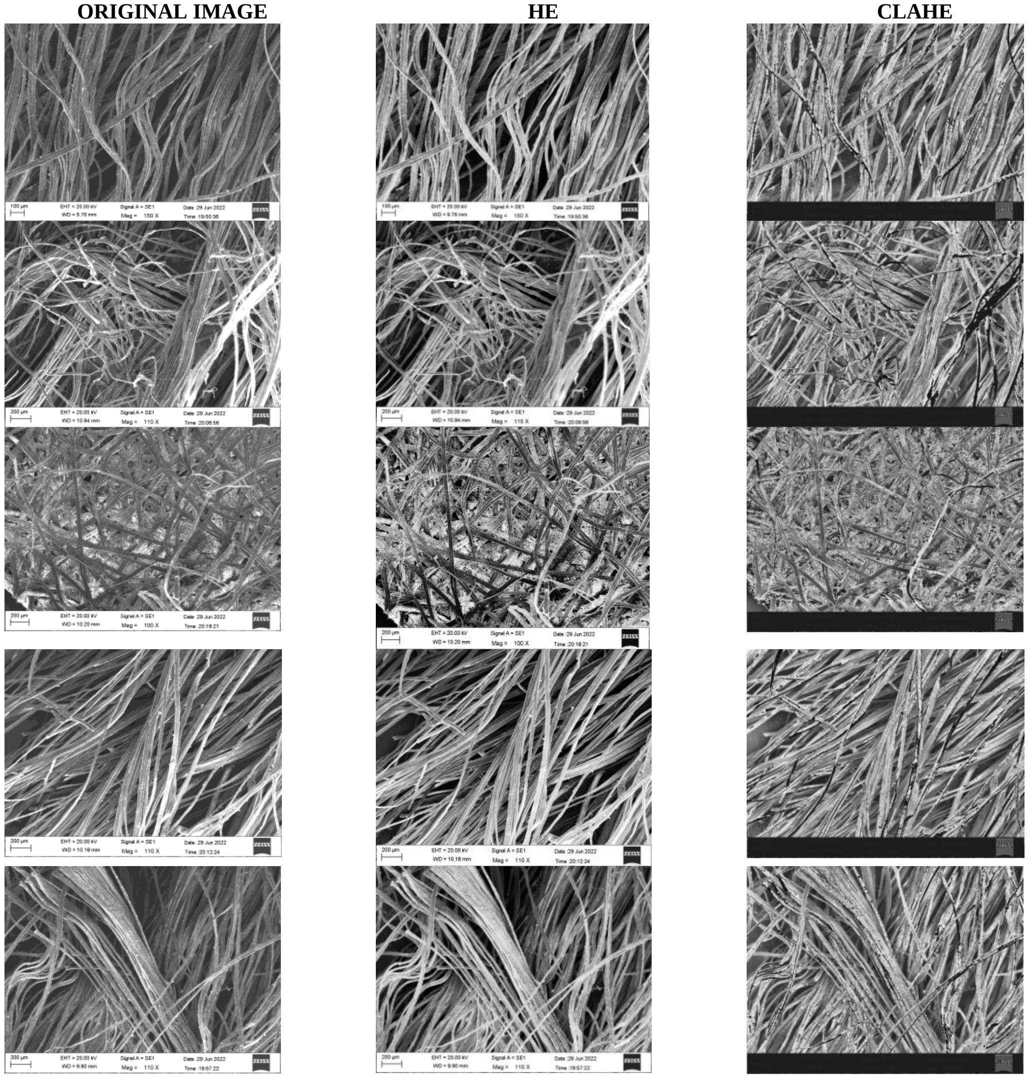


Fig. 7 The results of the CLAHE for the original images

5. Result and Discussions

To demonstrate the performance of our analysis in the tabular structure, where we have created three columns (Original Image, HE, and CLAHE), the first column is for the original images. After applying HE, we got the second image, which is in the second column, and lastly, the three columns contain the CLAHE Images. Observing the resultant images, we can clearly see that the CLAHE images are clearer compared to the original Image and HE image. HE made the image.

It is more whitish, but CLAHE cleared the image, and we can see that it made us see all the tiny details that are not visible in the original image and the HE Image. Figure 7 compares the original images of the microscopic longitudinal micro Muga silk with the corresponding improvements with the help of Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE). Column one depicts the original photographs, which demonstrate the naturalness of the silk fibers and the contrast of their nature.

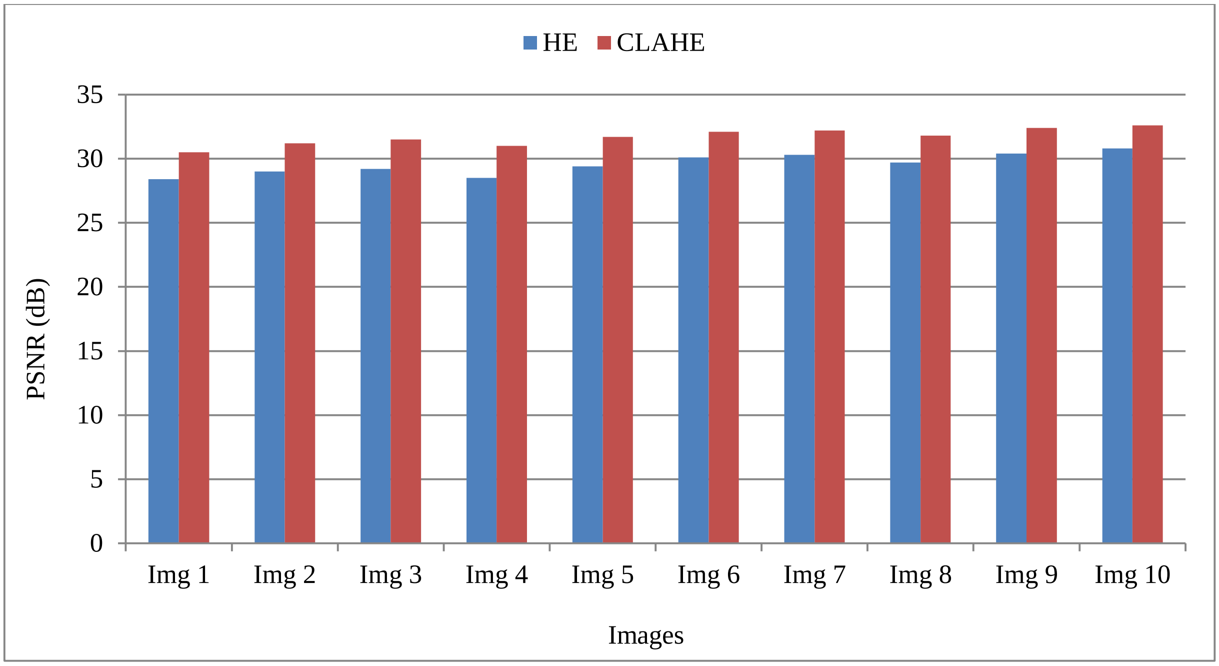


Fig. 8 Comparison of PSNR for HE and CLAHE

Fig. 9 PSNR for HE and CLAHE

The second column can be used to show the outcome of the application of HE with the global contrast being strengthened, but likely some locations will seem to be overstrengthened, which might influence the fine details of the fibers. The third column shows the outcome of the use of CLAHE, which increases the local contrast of various parts of the picture, retaining the tiny filament and the finer characteristics of the silk threads. Figure 8 shows a plot of the PSNR of HE and CLAHE in a range of images. An important measure of image quality is PSNR, and the larger its value, the higher the quality of the image. It is revealed by the plot that the CLAHE tends to be better in comparison with the HE, exhibiting an increased PSNR value for all photographs. This shows that the quality of the images is preserved by CLAHE as well as contrast improvement, which is more advantageous to the microscopic Muga silk images. In Figure 9, a plot is presented to illustrate variations of PSNR values of HE and CLAHE at various indices of an image.

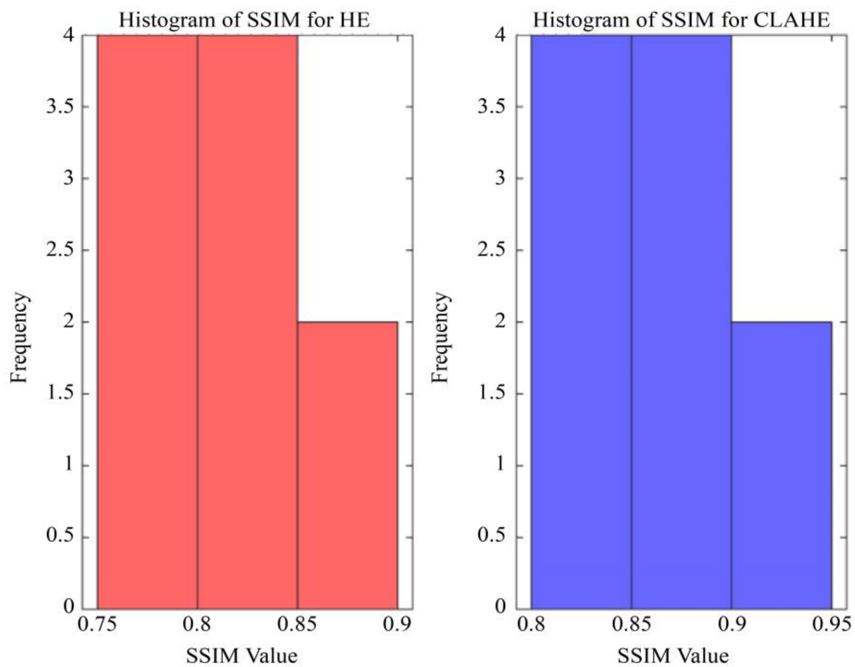


Fig. 10 Histogram of SSIM for HE and CLAHE

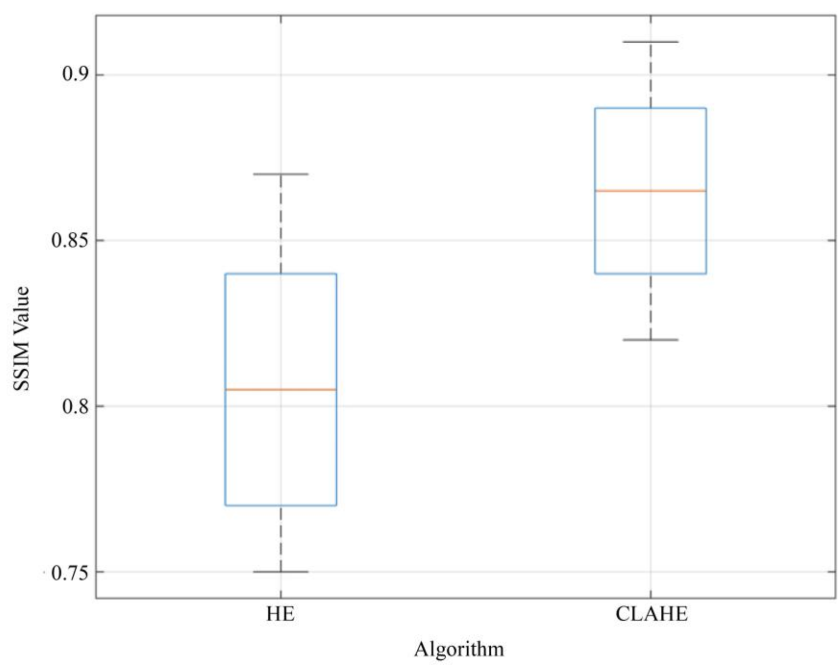


Fig. 11 Comparison of SSIM for HE and CLAHE

The performance of the two methods can be directly compared on several images using this visualization. The red line is a depiction of HE, and the blue line is a depiction of CLAHE. The plot shows clearly that CLAHE has always had high PSNR values as opposed to HE, supporting the conclusion made in Figure 8 that CLAHE is the best in terms of image quality amplification. In Figure 10, two histograms are provided, which show the distribution of the Structural Similarity Index (SSIM) values of HE and CLAHE. SSIM is an index of the subjective image quality that takes into account the luminance, contrast, and structure. The SSIM values of each image after processing with HE are represented by the left Histogram, whereas the SSIM value of each image after processing with CLAHE is indicated in the right Histogram. The Histogram of CLAHE has more dispersed values and a narrower distribution, and this implies that CLAHE is more efficient in preserving image structure compared to HE. This reiterates the point that CLAHE has the effect of improving the aesthetic appeal and the visual efficiency of the images.

Figure 11. shows the comparison of the plot of the SSIM values of HE and CLAHE, which gives a distinct visual image of the distribution of the SSIM scores of both algorithms. The plot demonstrates that CLAHE produces significantly larger median SSIM values than HE and fewer deviations and outliers, which implies that it not only enhances the quality of the pictures, but also does so more reliably. This value is in line with the previous results, which indicate that CLAHE has a high image enhancement rate in that it retains structural features in microscopic silk images.

6. Conclusion

The current paper introduces the CLAHE algorithm as one of the highly successful techniques that boost the contrast of the microscopic image of Muga silk. CLAHE, a better alternative to the classical histogram equalization, outdid the performance of the Histogram Equalization (HE) on image quality. The findings indicate that the average PSNR of CLAHE was 32.3 dB, much better than its counterpart, HE, which was 29.7 dB, and demonstrate that the overall image view of CLAHE was better with less distortion. Besides, CLAHE showed better results in maintaining the structural integrity of the images, with an average SSIM of 0.88 as opposed to the average SSIM of 0.80 of HE. These results imply that CLAHE is an efficient technique to increase the contrast of a microscopic silk image without neglecting fine detail, thus it is especially applicable to techniques that need to provide high-quality image analysis. Taking these findings into consideration, CLAHE would be a useful option towards enhancing the contrast and conserving the fine details of the microscopic images, particularly where accuracy is a key requirement, as in the case of textile analysis.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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