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Enhanced Contrast of Microscopic Blood Images of Leukaemia using a Modified Morphological Contrast Enhancement Algorithm

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Abstract: - The integration of image processing techniques greatly enhances diagnostic capabilities in medical imaging. Leukaemia, a widespread malignancy of the blood, affects both adults and children. Data indicate that leukaemia is the fifth and sixth leading cause of cancer deaths in men (7%) and women (5.8%), respectively. Currently, haematologists rely on microscopic examination of blood samples using light microscopy for diagnosis. This approach is labour-intensive, time-consuming, and impractical for analysing large volumes of cells. The challenge of detecting infected cells in low-contrast images further complicates automatic detection, often resulting in false positives. To address these limitations, we propose a method to enhance image contrast, thereby improving detection accuracy. Morphological Contrast Enhancement (MCE) is a pivotal technique in image processing, particularly within the medical field, designed to improve the contrast of microscopic blood images. Its primary objective is to enhance the visibility of critical features, such as leukemic cells, facilitating more accurate identification and diagnosis by pathologists. However, traditional MCE algorithms encounter difficulties due to varying lighting conditions, noise, and the inherent complexity of microscopic blood images. To mitigate these challenges, we propose the development of a Modified Morphological Contrast Enhancement (MMCE) algorithm to achieve superior performance and reliability. .

Keywords: Image processing, Morphological operations, contrast enhancement, Leukaemia, histogram equalization, microscopic blood images.

I. INTRODUCTION

Leukaemia is a form of blood cancer marked by the uncontrolled growth of white blood cells. It has been a leading cause of cancer-related deaths globally, accounting for about 3.4% of all new cancer cases and 3.8% of cancer-related fatalities [1]. Microscopic examination of blood smears is one of the primary methods used for diagnosing leukaemia. However, the quality of microscopic images can vary significantly due to factors such as staining techniques, lighting conditions, and the presence of noise [2]. This variability can make it difficult to identify leukemic cells, which often appear with low contrast against the background. Morphological operations, which are a subset of image processing techniques based on the shape or structure of objects within an image, have been widely used for enhancing the contrast in medical images [3].

Microscopic blood tests are the primary method used for diagnosing leukemia. While blood smear analysis is the most prevalent technique for detecting leukemia, it is not the only method available. Given the time and cost constraints of various techniques, microscopic blood tests and bone marrow analysis remain the most commonly employed approaches for identifying leukemia subtypes [4]. But low contrast is the biggest issue while automatic detection of infected cells. In the work, we have addressed this issue to improve the accuracy. Morphological Contrast Enhancement (MCE) involves applying morphological operators like dilation, erosion, opening, and closing to an image. These operators are used to highlight or suppress specific features based on their shape. In the context of leukaemia blood images, MCE can enhance the contrast between leukemic cells and the surrounding blood components. However, traditional MCE algorithms may not perform well under varying imaging conditions [5]. For instance, if the image has uneven lighting, the algorithm might fail to enhance certain areas, leading to poor contrast and potential misdiagnosis. Leukaemia microscopic blood images present several challenges for image processing algorithms:

i. Varying Lighting Conditions**:** Uneven illumination can cause parts of the image to appear too bright or too dark, making it difficult to enhance contrast uniformly.

ii. Noise**:** Microscopic images often contain noise, which can obscure important features and make it harder to distinguish between different cell types.

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iii. Complex Background**:** The background of a blood smear image is often cluttered with various blood components, making it challenging to isolate leukemic cells.

iv. Cell Overlap**:** In many cases, leukemic cells overlap with other cells or with each other, complicating the task of contrast enhancement.

Histogram Equalization (HE) is a widely used method for improving image contrast by adjusting the distribution of pixel intensity values. This technique achieves a more uniform histogram by levelingand expanding the most prevalent intensity values. It works by remapping the original intensity levels to new values according to the cumulative distribution function of the image's histogram [6]. As a result, areas of low contrast become more distinct, improving the overall visibility of details. Histogram equalization is particularly effective for images with poor contrast, making features more discernible. HE can sometimes lead to over enhancement of noise and artefacts, especially in images with already good contrast. It may also cause unnatural-looking images by overemphasizing certain features. Additionally, it can wash out details in areas with subtle contrast, leading to loss of information. This method may not be suitable for all types of images.

Adaptive Histogram Equalization (AHE) improves contrast by segmenting an image into smaller regions and performing histogram equalization on each segment separately. This method helps in highlighting local details, particularly in images with varying illumination [7]. AHE can effectively enhance details in specific areas without affecting the global contrast. However, a major drawback is that it can amplify noise in uniform regions, leading to grainy or overly enhanced textures. Additionally, AHE might produce artefacts along the boundaries of the small regions, resulting in an unnatural appearance. Contrast stretching increases the dynamic range of pixel intensities by scaling the image's histogram to cover the full intensity range (e.g., 0 to 255). This technique is straightforward and effective for improving contrast in images with a narrow intensity range [8]. However, it has limitations in images where the contrast is already spread across a wide range. In such cases, contrast stretching may not significantly enhance the image. Moreover, it can lead to clipping in areas where the intensity values are concentrated, losing important details.

Gamma correction modifies an image's brightness and contrast by applying a non-linear transformation to its pixel values. It’s often used to correct the brightness of images displayed on screens or to enhance specific intensity ranges. By modifying the gamma value, images can appear brighter or darker, improving contrast in mid-tones [9]. However, the technique can introduce unnatural brightness levels if not carefully applied, making the image appear washed out or too dark. It’s also less effective for images with already balanced contrast, where it might not provide significant improvement. Unsharp masking improves contrast by emphasizing edges in an image. It works by subtracting a blurred version of the image from the original, highlighting differences and making edges more pronounced. This technique is widely used in photography to enhance detail and sharpness [10]. However, it can introduce halo effects around edges, where bright and dark regions meet, and may also exaggerate noise, especially in already noisy images. Overuse of unsharp masking can lead to an unnatural, overly sharp appearance, diminishing the overall quality of the image.

CLAHE is an extension of AHE that limits the contrast amplification to avoid noise enhancement. It divides the image into small blocks and applies histogram equalization, but it clips the histogram at a predefined value to reduce noise. CLAHE is effective for enhancing local contrast without introducing significant noise. However, its drawbacks include the potential for blockiness, where the boundaries of the small regions become visible, especially in uniform areas. Additionally, improper setting of the clip limit can lead to either insufficient contrast enhancement or excessive noise suppression, depending on the image [11]. To overcome these traditional contrast enhancement techniques, we proposed a Modified Morphological Contrast Enhancement (MMCE)to enhance the contrast of low contrast blood microscopic images of leukaemia.

II. Modified Morphological Contrast Enhancement (MMCE) Algorithm

To address the challenges outlined above, a Modified Morphological Contrast Enhancement (MMCE) algorithm can be proposed. The MMCE algorithm enhances the contrast of leukaemia microscopic blood images by combining traditional morphological operations with additional pre-processing and post-processing steps. In traditional MCE, basic morphological operations like dilation, erosion, opening, and closing are applied directly to enhance the image based on the shapes and sizes of features [12]. The MMCE algorithm not only applies

these basic operations but also incorporates additional morphological transformations like top-hat and bottom hat transformations. These specific transformations enhance bright and dark features differently, making the algorithm more adaptable to complex images. The proposed MMCE is as shown in Fig.1. The algorithm can be broken down into the following steps. The input color blood image of size be represented by,

$$f(x,y) = \begin{bmatrix} f_R \\ f_G \\ f_B \end{bmatrix}_{m \times n} \quad (1)$$

Where *R,G,B* denote the red, green, and blue colour values of a pixel.

2.1. Pre-processing

2.1.1 Color Space Transformation

The color space transformation from RGB to grayscale can be mathematically represented by the following equation:

$$\mathrm{h}(x,y) = w_1 f_R(x,y) + w_2 f_G(x,y) + w_3 f_B(x,y) \quad (2)$$

where w_i are weights of red, green and blue channels.

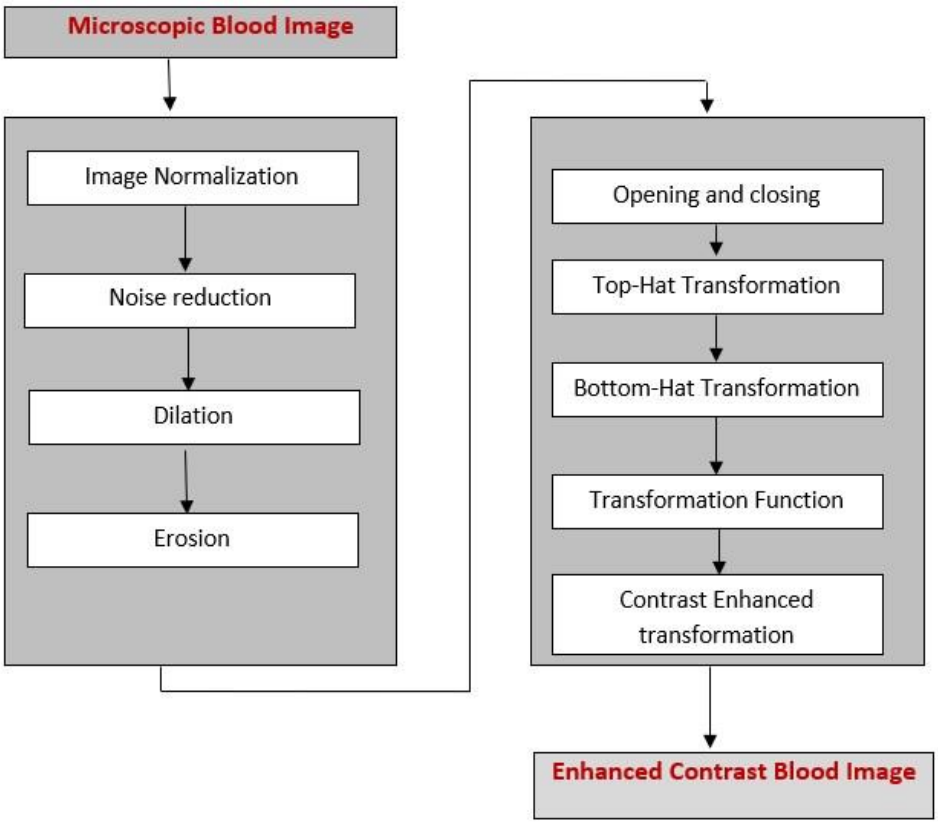

Fig.1: Flowchart of the proposed Modified Morphological Contrast Enhancement (MMCE)

2.1.2 Image Normalization

Image normalization is a crucial pre-processing step in analyzing microscopic leukemia blood images, aimed at reducing the impact of varying lighting conditions. This process standardizes pixel intensity values across an image, preventing variations in lighting from affecting the analysis [13]. Mathematically, normalization can be achieved using several techniques. A common approach is Min-Max normalization, where pixel values are scaled to a range between 0 and 1. The equation for this is:

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \quad (3)$$

where I represents the original pixel intensity, I_{min} and I_{max} are the minimum and maximum pixel values in the image, respectively, and I_{norm} is the normalized pixel intensity.

2.1.3 Noise Reduction

The median filter is a non-linear digital filter that reduces noise in an image while maintaining edge details. It achieves this by replacing each pixel's value with the median of the surrounding neighborhood pixels. This method is particularly effective for removing "salt and pepper" noise [14]. The main goal is to Remove noise from an image by replacing each pixel with the middle value from its surrounding pixels. The median algorithm is as follows.

Step 1: (Padding) Add extra pixels around the edges of the image so that every pixel, even at the edges, has neighbors.

Step 2: (Sliding Window**)** Move a small square window, like 3×3 , over each pixel in the image. This window includes the

pixel and its surrounding pixels.

Step 3: (Find the Median) Collect the pixel values within the window and sort these values and pick the middle one. This

middle value is called the median. Replace the original pixel value with the median value you found.

$$I_m\,(f(x,y)) = Median(x,y) \quad (4)$$

Step 4: (Repeat) Do this for every pixel in the image.

Step 5: **(**output**)** The new image is less noisy because the median filter smooths out sudden changes in pixel values.

The resulting image $I_m\,(f(x,y))$ is the output of the median filter.

This process helps to smooth out noise while maintaining sharpness at edges, as the median operation is less sensitive to extreme values compared to averaging filters [15].

2.2 Morphological Operations

2.2.1Dilation and Erosion

Dilation is used to expand the bright regions in the image, making them more prominent, while erosion is used to shrink the dark regions. These operations help to further enhance the contrast between leukemic cells and the background. Dilation enlarges the boundaries of objects in an image [16]. It works by placing a structuring element (a small shape or matrix) over each pixel in the image. If the structuring element overlaps any part of the object (foreground), the pixel in the output image is set to the maximum value (typically white in binary images). Erosion shrinks the boundaries of objects in an image. It involves placing the structuring element over each pixel in the image [19]. If the structuring element fits entirely within the object, the pixel remains; otherwise, it's removed or set to the minimum value (typically black in binary images). Erosion followed by dilation, used to remove small objects or noise. Dilation followed by erosion, used to fill small holes and connect adjacent objects [20].

2.2.2 Opening and Closing

These operations are applied to smooth the image, remove small objects, and fill in small gaps. Opening is performed after erosion to remove noise, and closing is performed after dilation to fill gaps and smooth the contours of leukemic cells. Opening andClosing are morphological operations used to process binary and grayscale images, focusing on removing noise and shaping object boundaries [21]. Opening is an operation that removes small objects from an image while preserving the shape and size of larger objects. It consists of two steps: The image is eroded using a structuring element. This step reduces the size of the foreground objects and removes small noise. The eroded image is then dilated using the same structuring element. This step restores the

size of the larger objects, closing up small gaps that erosion created. Closing is an operation that fills small holes and gaps within objects [17]. It consists of two steps: The image is dilated using a structuring element. This step enlarges the foreground objects and fills small gaps or holes. The dilated image is then eroded using the same structuring element [18]. This step restores the size of the objects while maintaining the filled gaps.

2.3 Top-Hat Transformation

The Top-Hat Transformation is a morphological image processing technique used to highlight features of a specific size or shape by subtracting the results of morphological operations from the original image[21]. It enhances contrast between the features of interest and the background, making it useful for tasks such as defect detection or feature extraction.The transformation involves two primary operations: morphological opening and closing. Given an image I and a structuring element B, the morphological opening $I \circ B$ is defined as:

$$I \circ B = (I \ominus B) \oplus B \quad (5)$$

Where $\ominus$ denotes dilation and $\oplus$ denotes erosion. The Top-Hat Transformation T is then computed as:

$$T_{TH}(I) = I - (I \circ B) \quad (6)$$

This operation subtracts the result of the morphological opening from the original image, effectively highlighting bright regions that were significantly reduced by the opening process. It is particularly effective for revealing small, bright objects on a darker background, making it valuable for applications in image analysis, medical imaging, and defect detection.

2.4 Bottom-Hat Transformations

These transformations are applied to enhance bright and dark features, respectively. The top-hat transformation highlights small bright regions (potential leukemic cells), while the bottomhat transformation enhances small dark regions [22]. The Bottom-Hat Transformation is a morphological image processing technique used to enhance dark features on a bright background. It is particularly useful for highlighting small, dark objects or regions within an image. To compute the Bottom-Hat Transformation, you need an image II and a structuring element BB. The transformation involves morphological closing. Bottom-Hat Transformation TT is then computed as:

$$\text{II.} \quad T_{BH}(I) = (I \oplus B) - I \quad (7)$$

This operation subtracts the original image from the result of the morphological closing. The Bottom-Hat Transformation enhances dark regions against a bright background, making it useful for detecting small, dark features that are otherwise hard to distinguish.

***2.5** Contrast Enhanced Image*

The combined contrast-enhanced image is computed by adding the scaled Top-Hat result and subtracting the scaled Bottom-Hat result from the original image:

$$I_{Enhanced} = I + \alpha T_{TH} - \beta T_{BH} \quad (8)$$

where α and β are scaling factors. These factors adjust the contribution of each transformation to the final image. α scales the influence of the Top-Hat Transformation, amplifying bright features and β scales the influence of the Bottom-Hat Transformation, enhancing dark features. The combination effectively amplifies both bright and dark features. By adjusting α and β, we can finetune the enhancement to emphasize specific features and improve overall contrast [23]. This approach provides a balanced enhancement by addressing both types of features, which is crucial for applications like image analysis and feature extraction. This combination amplifies both bright and dark features, improving overall contrast and visibility. Adjusting α and β allows for finetuning of feature enhancement. The Modified Morphological Contrast Enhancement (MMCE) algorithm offers several advantages over traditional MCE techniques: Improved Contrast in Varying Conditions, Better Cell Isolation, Enhanced Visibility of Overlapping Cells, and Scalability.

III. EXPERIMENTAL RESULTS:

The proposed method is evaluated by using the measures Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Besides, we compared with the traditional enhancement methods. PSNR is a metric used to measure the quality of image reconstruction or enhancement by comparing it to a reference (original) image. It gauges the ratio between the maximum possible pixel value and the level of noise introduced during processing. The PSNR value is expressed in decibels (dB); higher values indicate better quality and less distortion. Essentially, PSNR reflects how closely the enhanced image matches the original one, focusing on pixel-wise accuracy [24]. However, PSNR can sometimes fail to align with perceptual quality, as it doesn't account for how the human eye perceives differences in images.

$$PSNR = 10.log_{10}({}^{R^2}/_{MSE}) \quad (9)$$

SSIM assesses image quality by evaluating the structural similarity between the original and enhanced images. It considers three key aspects: luminance, contrast, and structural information. Unlike PSNR, SSIM is designed to be more in line with human visual perception. It measures how well the local patterns of pixel intensities match between the images, accounting for factors such as lighting and contrast variations. SSIM values range from -1 to 1, where 1 signifies perfect similarity. By focusing on structural information rather than just pixel differences, SSIM often provides a better representation of perceived image quality.

$$SSIM\ [f(x,y), g(x,y)] = L(f,g) * C(f,g) * S(f,g) \quad (10)$$

Where $C(f,\ g)$ indicates contrast comparison function, $S(f,\ g)$ represents structure comparison function and $L(f,g)$ indicates luminance comparison functions [24].

The PSNR value achieved by the proposed MMCE surpasses those obtained with HE, AHE, CLAHE and Gamma correction. A higher PSNR generally indicates that the enhanced or reconstructed image more closely resembles the original, with reduced distortion or error, suggesting that the image quality is superior and the alterations introduced by MMCE are minimal.

Additionally, the average SSIM value of 0.85 for the proposed MMCE implies a strong similarity between the processed images and the originals, with only minor variations in contrast, brightness, or structure. These differences are typically imperceptible to the human eye, particularly when compared to other contrast enhancement techniques like Histogram Equalization, AHE, CLAHE, and gamma correction

IV. Conclusion

In this paper, we have proposed the Modified Morphological Contrast Enhancement (MMCE) algorithm provides a significant improvement over traditional MCE techniques for enhancing the contrast of leukaemia microscopic blood images. The research developed a Modified Morphological Contrast Enhancement (MMCE) algorithm to address the challenges in enhancing the contrast of microscopic blood images for leukaemia diagnosis. Traditional techniques such as HE, AHE, CLAHE and Gamma Correction have limitations under varying imaging conditions, including inconsistent lighting, noise, and overlapping cells. MMCE improves contrast by combining basic morphological operations—dilation, erosion, opening, and closing—with advanced transformations like top-hat and bottom-hat. This approach effectively enhances both bright and dark features, adapting better to complex image conditions. Pre-processing steps like color space transformation, normalization, and noise reduction with median filtering further refine the images before enhancement. Experimental results show that MMCE achieves higher PSNR values, indicating improved image quality with minimal distortion. The average Structural Similarity Index (SSIM) value of 0.85 reflects high structural similarity and perceptual quality, ensuring that enhanced images closely resemble the originals and maintain important details. In summary, MMCE provides a significant improvement in contrast enhancement for leukaemia

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