International Journal of Advance and Innovative Research
Volume 13, Issue 1 (XIII): January – March 2026
ISSN 2394 - 7780

DETERMINATION OF OPTIMAL APPROACH BY COMPREHENSIVE EVALUATION OF NOISE REDUCTION METHODS FOR ACUTE LYMPHOBLASTIC LEUKEMIA AND ITS SUB TYPES

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ABSTRACT
The precise improvement of microscopic blood smear pictures plays a major role in the dectection of Acute Lymphoblastic Leukemia (ALL), as the image noise and low contrast could hide morphologically important features like the shape, size, and texture of the nuclei. In this paper, we discuss a comparative study of contrast enhancement and noise filtering methods proposed at enhancing the visual quality and diagnostic dependability of ALL images. Contrast Stretching, Adaptive Histogram Equalization (AHE), and Contrast Limited Adaptive Histogram Equalization (CLAHE) were the methods tested for contrast enhancement. At the same time, numerous filters such as Mean, Median, Gaussian, Bilateral, Wiener, and Adaptive Median were considered for noise removal. The experimentation was done on the ALL, IDB dataset, and the results were assessed in terms of quantitative metrics such as Peak Signal, to, Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index (SSIM), Signal, to, Noise Ratio (SNR), and Universal Quality Measurement (UQM). The experimental results reveal that Contrast Stretching gives better outcomes in terms of contrast enhancement with less loss of structures. Also, the Adaptive Median filter is most effective in noise removal while preserving significant morphological features. When Contrast Stretching and Adaptive Median filtering are used together, it results in greatly enhanced image clarity and the features important for diagnosis becomes more visible. These results emphasize the role of proper preprocessing procedures in automated leukemia detection as well as in helping clinical diagnosis.

Keywords: *Acute Lymphoblastic Leukemia, Deep learning, Mean Squared Error, Peak Signal-to-Noise Ratio, Filters*

1. INTRODUCTION
Blood analysis is crucial for medical diagnostics because variations in the amounts of these components in a sample may provide significant details about the origins of different diseases [1]. Acute lymphoblastic leukemia (ALL) is a fast-growing blood cancer that results in a proliferation of lymphoblasts, that constitute immature white blood cells, and hence disrupts with the process of producing healthy red blood cells. The immune system is weakened by this cancer, which increases the risk of it spreading to critical organs such the kidneys, lungs, liver, spleen, and brain [2]. Some genetic variations, radiation exposure, and chemical exposure increase the risk of developing ALL [3], which has more frequent occurrence in children but also prevalent in adults. The

vague symptoms of acute lymphoblastic leukemia (ALL) can make a preliminary diagnosis difficult since they are so similar to those of other diseases, such as influenza and anemia. Lymph node enlargement, fatigue, fever, frequent infections, and unexplained weight loss are all possible symptoms; however, some people may not experience any symptoms at all [4]. To increase survival rates and provide appropriate treatment, early detection is crucial. Cancers like leukemia often develop in the bone marrow and blood, the organs responsible for making new blood cells [5, 6]. Leukemia cell morphology, including nucleus size and shape, cytoplasmic characteristics, and the presence of nucleoli, further ALL is categories into three subtypes: L1, L2, and L3 [7][8]. The **Table 1.** provides a morphological classification of Acute Lymphocytic Leukemia (ALL) according to the FAB system and it also highlights the main characteristics of L1, L2, and L3 blast cells.

The differences among these subtypes are based on cell size, the volume of cytoplasm, and nucleoli visibility that are essential for precise microscopic diagnosis and analysis. **Figure 1.** depicts the various morphologies of the three subtypes of ALL (Acute Lymphoblastic Leukemia): L1, L2, and L3. The L1 subtype is characterized by small, uniform lymphoblasts, while the L2 subtype displays large, scattered cells that vary greatly in size and shape. In L3, the cells are large and exhibit prominent nucleoli and cytoplasmic vacuoles. These features are essential for accurate diagnosis and automated classification of all subtypes.

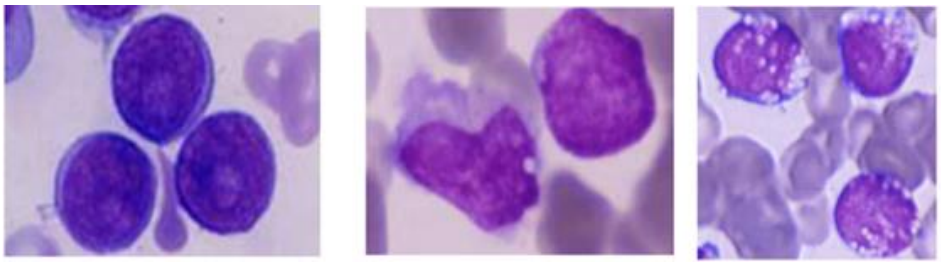
Table 1. Morphological Classification of Acute Lymphocytic Leukemia

FAB Type	Features of Blasts [7]
L1	Compact cells with little cytoplasm have overlapping and insignificant nucleoli.
L2	Numerous distinct cells with a medium volume of cytoplasm, a gap and notch in the center of the nucleus, and numerous, apparent nucleoli.

ISSN 2394 - 7780

L3	These kinds of cells are the biggest, having noticeable nucleoli and a substantial amount of vacuole cytoplasm.

Type L1 is the predominant form of acute leukemia in children, comprising 74% of instances among individuals aged 15 and below. Leukemia type L2 comprises 66% of acute leukemia cases in individuals aged 15 years and above. The prevalence of Type L3 is very low, accounting for approximately 1-2% of all instances of acute lymphoblastic leukemia (ALL). Fig.1 graphically illustrates the many subtypes of ALL.



(a) **(b)** **(c)**

Figure. 1. Morphology of Acute Lymphoblastic Leukemia Subtypes images [8]: (a) L1 (b) L2 and (c) L3

The most suitable and proper research gaps in this field:

1. Lack of denoising methods specifically for certain subtypes.
There are several existing denoising methods that have been designed for general medical imaging or blood smear images at large, which do not particularly cater to all subtypes (L1, L2, and L3). The present methods do not consider different morphological features of the various ALL subtypes, which could be changed through a denoising step. The issue is that if the image gets too smooth, the essential diagnostic features such as nuclear morphology, chromatin texture and cellular borders can be lost.

2. Traditional filters make important diagnostic features worse.
Traditional filters like mean, median, and Gaussian not only reduce noise but also make edges less sharp and remove small details that are important for diagnosis, which makes the diagnosis less accurate. So, we need noise removal methods that can get rid of noise quickly while also keeping the important parts and structures of clinical diagnosis.

3. Restricted evaluation exclusively on ALL datasets
Most denoising studies are evaluated using generic, natural, or non-leukemic medical images instead of all microscopic datasets. That has led to a research gap because not much has been done to evaluate the denoising outcome on ALL images with appropriate quality parameters.

4. Absence of comparison study of spatial filters for all subtype images
Most studies use only one or two spatial filters and fail to evaluate multiple filters like Mean, Median, Gaussian, and Wiener on all subtype images adequately. This makes it difficult to determine the most efficient filter using standard metrics like MSE, PSNR, and SSIM.

5. The effect of noise on the classification of automated ALL subtypes remains inadequately explored.
Noise makes it more difficult to segment, extract features, and classify ALL subtype images. Nonetheless, the effect of denoising on enhancing classification accuracy remains inadequately explored.

6. No optimised or hybrid denoising techniques exist particularly for ALL images.
The majority of research employ traditional denoising filters that fail to perform well with ALL Subtypes types microscopic images. This makes it more difficult for researchers to develop the hybrid or optimised techniques that better keep important diagnostic features.

2. LITERATURE REVIEW

The hue and brightness of blood smear images seen under a microscope are adjusted to an acceptable standard by stain normalization. It minimizes the variations that come from using different cameras, lighting, and illumination. This improves image segmentation and classification, which ensures accurate evaluation in an extensive variety of imaging conditions. [13] [14]. Histogram normalisation enhances contrast however could increase noise in sensitive applications. AHE and CLAHE enhance contrast while preserving details by adjusting local pixel intensities. These approaches rectify uneven lighting, however they can exacerbate noise and artefacts. [15] [16]. Gehlot et al. [17] introduced an innovative coupled network consists of two U-Net modules that employs self-supervised learning for image reconstruction and stain normalization. AimiSalihah et al. [18] suggested the utilization of contrast stretching to improve the differentiation between ALL and AML

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cells by enhancing image features and highlighting morphological characteristics for leukemia cell detection. Himali P. Vaghela et al. [19] applied histogram equalisation, contrast stretching, and morphological operations to classify leukemia cells, obtaining 72% accuracy with K-means clustering, despite the absence of labelled data classification. Pradeep Kumar Das et al. [20] and Xu Jingbo et al. [21] applied Laplacian-of-Gaussian (LoG) and LoG-based modified high boosting (LoGMH) techniques to enhance image quality for the purpose of detecting white and overlapping cells. As a result of reducing noise and improving edge detection, they achieved 97.8% accuracy. Niranjana Sampathila et al. [22] achieved 95.54% precision and 95.91% sensitivity by transforming images to HIS colour space for enhanced contrast, in order to segment white blood cells and detect leukemia, using the ALL Challenge dataset and a CNN classifier. Raheel Baig et al. [23] suggest a technique for the diagnosis of leukemia using enhanced blood stain images. The bagging ensemble algorithm was utilized to achieve 97.04% precision after preprocessing, segmentation, and CNN feature extraction. Tulasi Gayatri Devi et al. [24] developed the GBHSVLeuk technique, which combines Gaussian Blurring and HSV techniques for ALL cell segmentation. The technique achieved 96.30% and 95.41% accuracy on private and public datasets, respectively. Fabio Scotti [25] have reconstructed the background of images using 400-pixel-sigma-parameter Gaussian low-pass filter. Abdul Nasir et al. [29] suggested the use of a Gaussian filter and pixel elimination method to reduce noise, as well as to smooth and remove small objects under 100 pixels from binary images while preserving all boundaries. Subrajeet Mohapatra et al. [26] implemented a twostep procedure: unsharp masking and selective median filtering to reduce image noise caused by extensive staining. This technique, that had been modified to incorporate adaptive thresholds for noise detection, substantially enhanced the quality of images for precise analysis. Adnan Khashman and Hayder Hassan [27] used Otsu's thresholding to convert greyscale images to binary, implemented a median filter to minimise noise, and then passed the results to a neural classifier using the Canny operator for edge detection. In their study, Minal Joshi and et. al [28] improvise the contrast of greyscale images by applying histogram equalisation and linear contrast stretching, segmented the image to separate the blood components, utilised a 3x3 minimum filter to minimise noise and preserve edges, and subsequently used Otsu's method for global thresholding to convert the filtered image into binary format. Reham Mohammed et al. [29] proposed converting RGB to C-Y colour space, extracting the Y illuminance component, applying histogram-based thresholding and a 5x5 median filter, and converting back to RGB for display to segment any colour images. Ashutosh Mishra and Nimesh Patel [30] used a median filter to get rid of noise and a Wiener filter to get rid of blurriness. They then cleaned up the images by testing their solidity after they were converted to greyscale. Madhloom [31] used a median filter for the enhancement of pixel discontinuities in the b component of an image. Sonali Mishra et al. [32] utilized histogram equalisation to locate regions of interest, a Wiener filter to enhance images, and thresholding to retain only the WBC component in binary images. Jyoti Rawat et al. [33] used histogram equalization for the enhancement of image quality and a 2-D statistical filter for the denoising in the image. Tahmina Akter Sumi et al. [34] utilized a median filter to eliminate the nose and histogram equalization to enhance the image. In their proposed optimal deep transfer learning-based human-centric biomedical diagnosis model for acute lymphoblastic detection (ODLHBD-ALLD), Manar Ahmed Hamza et. al [35] implemented the Gabor Filtering (GF) method to eliminate image noise. Based upon the literature survey, it has been observed that the most researcher [36] has used the spatial filters for removal of the noise in the blood smear images Accordingly we have applied spatial filters with our blood smear images datasets of ALL in order to evaluate the performance metrics based on MSE, SNR and PSNR to determine which techniques gives the optimum results. Conventional spatial domain filters like the mean, median, and Gaussian are computationally simple and quite effective for removing basic noise; still, they tend to blur edges and erase some important diagnostic features. However, deep learning methods such as Convolutional Neural Networks (CNNs) can achieve better feature preservation and adaptively perform denoising but need lots of annotated datasets and powerful computing resources. Baig R et. al [39]Adaptive Histogram Equalization (AHE) is a technique of image processing, which enhances the contrast of color films of the blood smears under the microscope by dividing the image into smaller regions and then individually enhancing the contrast of these small regions, which makes the leukemic lymphoblast cells more visible for accurate detection of Acute Lymphoblastic Leukemia (ALL). Nevertheless, it can also lead to more noise in homogeneous areas, but it is still a vital method of preprocessing leukemia images. Zuiderveld [40] proposed Contrast Limited Adaptive Histogram Equalization (CLAHE), a technique that enhances the contrast of images and at the same time limits noise amplification. It is a very useful approach for Acute Lymphoblastic Leukemia (ALL) microscopic images because it helps to better distinguish cellular structures and features that are of great importance to morphology and hence the analysis of the sample becomes more accurate. Buades et al. [41] proposed the Non-Local Means (NLM) algorithm, which eliminates noise from images by averaging similar region while keeping edges and textures. This method is also specifically useful for microscopic images of Acute Lymphoblastic Leukemia (ALL), where preserving the subtle morphological features is essential for

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an accurate diagnosis. BM3D is an algorithm proposed by Dabov et al. [42] to denoise images by grouping similar image blocks and performing collaborative filtering on these groups while still preserving the structural details of the image. The method has been proven to work well for ALL microscopic images since it helps keep the important cellular morphology which is crucial for diagnosis. Dong et al. [43] presented SRCNN, a deep learning model that super, resolves images by learning the feature mappings. This model helps to clarify the images of micrscopic cells of Acute Lymphoblastic Leukemia (ALL) and thus aids in better visualization of the cell structures. Zhang et al. [44] have designed DnCNN, a deep convolutional neural network that can efficiently remove the noise while keeping the important image features intact. It, therefore, can be considered as a method for enhancing the quality of ALL microscopic images. Besides, Zhang et al. [45] have come up with a hybrid technique that fuses CNN denoisers with conventional optimization methods, which leads to a goof noise removal that at the same time keeps the significant morphological details of the ALL images. Ledig et al. [46] have proposed SRGAN, which employs generative adversarial networks to improve image quality and texture, thus enabling to preserve the fine cellular details in ALL microscopic images for the accurate analysis. Pui et al. [47] gave a full account of Acute Lymphoblastic Leukemia (ALL), including its causes, diagnosis, and treatment, pointing out that ALL is the commonest childhood leukemia and is due to abnormal lymphocyte proliferation. Inaba et al. [48] detailed the genetic and molecular mechanisms of ALL and stressed the significance of diagnostic tools such as blood tests and bone marrow examination for the correct diagnosis and treatment. Putzu et al. [48] proposed classification system for a leukocyte depends on image processing which could utilize for enhancing the precision and speed of detection of ALL from microscopic blood images. Mohapatra et al. [50] demonstrated a method of automatic detection of ALL by the use of machine learning with image features and Support Vector Machine (SVM), thus attaining a very good level of classification accuracy. Shafique and Tehsin [51] applied Convolutional Neural Networks (CNN) to the task of detecting ALL automatically and thus raise the accuracy of diagnosis by the network learning the relevant image features on its own. Rehman et al. [52] have classified ALL cells from microscopic images by the use of deep learning models thus significantly improving the diagnostic performance and facilitating automated medical analysis. Labati et al. [53] presented the ALL, IDB dataset, which contains microscopic blood images that have been extensively used for the development and benchmarking of automated ALL detection methods and image processing techniques.

3. FILTERING AND ENHANCEMENT TECHNIQUES

There are numerous techniques for eliminating the noise from the blood smear images of Acute Lymphoblastic Leukemia (ALL). An improvement in the digital blood smear image of ALL can be obtained by utilizing the spatial domain filter. This paper will provide a more detailed discussion of certain frequently used spatial domain filters.

3.1. Gaussian Filter

A Gaussian filter, using a bell-shaped Gaussian function, smooths images by reducing noise and blur through convolution with a Gaussian kernel. The equation for the 2D Gaussian function can be mathematically formulate as:

$$G_\sigma(x,y) = \frac{1}{2\pi\sigma^2}\ e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

Where:

$G_\sigma(x,y) =$ Gaussian function at position (x.y)

$\sigma =$ Standard deviation (controls the amount of smoothing))

$\pi =$ Constant (≈ 3.14159)

$e =$ Euler's exponential constant

x, y= Spatial coordinates from the center of the kernel

The degree of visual smoothing in a Gaussian filter is determined by the standard deviation, where higher values result in increased blur but do not notably eliminate salt and pepper noise.

3.2. Mean Filter

A mean filter makes images smoother by taking the pixel's mean values of the pixels next to each other in a sliding window and giving that average value to the central pixel. The Mean Filter can be expressed mathematically by formula:

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$\widehat{f}(x,y) = \frac{1}{mn} \sum_{(s,t)\in S_{x,y}} g(s,t)$ (2)

Where:

$\widehat{f}(x,y) =$ Filtered image pixel at location (x,y)

$g(s,t) =$ Neighborhood pixel values.

$s_{x,y}$ = Set of coordinates in the neighborhood window centered at (x,y)

$mxn =$ the filter's window or kernel size.

The mean filter smooths images by averaging pixels in a defined kernel size, but larger kernels can blur details and are ineffective against salt and pepper noise.

3.3. Median Filter

A median filter eliminates the salt and pepper noise without blurring by substituting every pixel by the median value of its neighbouring area. This preserves edges and reduces noise. The following equation can be used for demonstrating the Median Filter:

$\widehat{f}(x,y) = median_{(s,t)\in S_{x,y}}\{g(s,t)\}$ (3)

Where:

$\widehat{f}(x,y) =$ Filtered image pixel at location (x,y).

$g(s,t) =$ Neighborhood pixel values.

$s_{x,y}$ = Set of coordinates in the neighborhood window centered at (x,y).

$median$ =Median value of all pixels in the window.

3.4. Bilateral Filter

Bilateral filters are nonlinear filters employed in the processing of images that improve edges and smaller details by combining nearby pixels with respect to the spatial distance and levels of contrast, as the bilateral filter equation says.

$BF[I]_p = \frac{1}{W_p} \sum_{q\in S} G_{\sigma_s}(\| p-q \|) G_{\sigma_r}(|I_p - I_q|) I_q$ (4)

Where:

$BF[I]_p =$ Intensity of the filtered image at pixel p

$W_p =$ Intensity of the filtered image at pixel p

$S =$ Neighborhood window around pixel p.

$P, q =$ Location of pixel.

$I_p, I_q =$ Intensity of pixel p and q.

$G_{\sigma_s} =$ Spatial function of Gaussian.

$G_{\sigma_r} =$ Range function of Gaussian.

$\sigma_s =$ Spatial standard deviation.

$\sigma_r =$ Intensity standard deviation.

$\| p-q \| =$ Intensity standard deviation.

Where as W_p is called as Normalization factor, $G_{\sigma_s}(\| p-q \|)$ is known as Space Weight

$G_{\sigma_r}(|I_p - I_q|)$ is known as the Range Weight

3.5. Wiener Filter

The Wiener filter reduces Gaussian noise through the reduction of among the primary signal input and the resultant outcomes. Adaptive Wiener filtering improves on the linear model by adjusting based on local image variance for better noise reduction. The formula for the Wiener filter is:

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$$H(u,v) = \frac{R\_f(u,v)}{\left[R\_f(u,v) + \frac{R\_n(u,v)}{K}\right]} \quad (5)$$

Where:

H(u,v) represent the spectral response of the filter at frequency coordinates *(u,v)*

R_f(u,v) denotes to the spectral power distribution of the signal .

R_n(u,v) signifies the noise power spectral density.

K regulates the ratio among noise elimination and distortion of signals.

3.6. Adaptive Median Filter

An adaptive median filter is a powerful nonlinear filtering method is capable of eliminating impulse noise and maintaining the edges of an image. The basic operation of the filter is to find the median of the neighborhood and then check it against the value of the current pixel. the Adaptive Median filter is defined in the spatial domain by following equation:

$$J(x,y) = \begin{cases} I(x,y), & if\ (|(x,y) - M(x,y)| < T \\ M(x,y), & otherwise \end{cases} \quad (6)$$

Where: M(x,y) represent the median intensity.

T is Predefined threshold.

This adaptive technique eliminates the presence of noise effectively while keeping important details about the structure.

3.7. Adaptive Histogram Equalization (AHE)

AHE relies on specific segments of the image (tiles) instead of the complete images.

The transformed intensity s is for a pixel intensity r in a local area:

$$s = (L-1)\sum_{k=0}^{r} pr^k \quad (7)$$

L = the number of gray levels

$pr^{(k)}$ = The probability density function (PDF) of the intensity level k in the surrounding area

r = The brightness of the input pixel.

s = Output pixel intensity.

Expanded form:

$$pr^{(k)} = \frac{n_k}{N}$$

$$s = (L-1)\sum_{k=0}^{r} \frac{n_k}{N}$$

n_k= The total amount of pixels in the region that possess an intensity of k.

N = The total amount of pixels in the local area.

3.8. Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE is like AHE, but it uses a clip limit to prevent histogram amplification.

First, the histogram is clipped:

$$H_c(k) = \begin{cases} H(k), & if\ H(k) \le T \\ T, & if\ H(k) > T \end{cases} \quad (8)$$

Where,

$H(k) =$ Original histogram

$H_c(k) =$ Clipped histogram

$T =$ Clip limit

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Then normalized:

$$P_{c(k)} = \frac{H_c(k)}{N}$$

Final intensity mapping:

$$s = (L-1)\sum_{k=0}^{r} p_c(k)$$

3.9. Contrast Stretching (Linear Contrast Stretching)

Contrast stretching enhances contrast better by extending the range of intensity.

$$s = (L-1)\frac{r-r_{min}}{r_{max}-r_{min}}x(L-1) \quad (9)$$

Where:

r = the brightness of the input pixel.

s = the brightness of the output pixel.

r_{min}= the lowest level of brightness in the input image.

r_{max} = highest brightness in the input image.

L = the number of gray levels.

In Acute Lymphoblastic Leukemia (ALL) detection, the accuracy of the diagnosis is largely dependent on identifying the morphological features that are most characteristic of the disease, such as the shape, size of the nucleus, chromatin texture, and the boundaries of the cells. Since images have noise, their preprocessing is inevitable; however, the use of the wrong filters may end up changing these features that are very critical. These filters work in different ways: for instance, the Gaussian filters not only help to reduce the noise but also cause the blurring of the nucleus edges; whereas the Median and CLAHE do a better job in keeping the structural details intact. Hence, it is very important to choose the filter that will help to enhance the quality of the images without leading to the loss of the diagnostic information. One of the ways to determine the optimal filter is by the comparative evaluation method through the use of visual analysis and quality metrics, e.g., PSNR and SSIM. By so doing, the reliability and accuracy of ALL detection and classification will be greatly enhanced.

4. DATASET

The datasets, which contained microscopic blood sample images associated with Acute Lymphoblastic Leukemia. An initial group of 20 images was collected, followed by 20 images from each of the three ALL subtypes (L1, L2, and L3), for a total of 60 images. The Acute Lymphoblastic Leukemia (ALL) dataset was obtained from the publicly available ALL-IDB, which was created by Professor Fabio Scotti at the University of Milan specifically for the purpose of doing image processing research. The use of these images for research has been permitted by Professor Scotti, with the condition that they are not used for diagnostic reasons. Furthermore, Dr. Ashwini Jogade, the Medical Superintendent of Nanavati Max Super Specialty Hospital in Mumbai, provided crucial specific expertise, therefore providing an accurate and specific approach to the research.

5. EXPERIMENTAL SETUP AND REPRODUCIBILITY

The experimental setup has been detailed in the paper to allow reproducibility and remove any ambiguity. It features all noise parameters, filter kernel sizes, and even the implementation environment used for image enhancement of Acute Lymphoblastic Leukemia (ALL) microscopic images. Besides, in order to make the images more realistic, in the paper have introduced Gaussian noise having mean = 0, variance = 0.02 and Salt, and, Pepper noise having density = 0.02 , while at the same time, the key morphological features remain uninterrupted. Different spatial filters such as Median Filter (3 x3), Gaussian Filter (5x 5 σ, = 1.0), and Adaptive Median Filter (maximum window size 7x 7) were used to get rid of noise while retaining the image's structural details. Besides, contrast enhancement gained from Contrast Stretching and CLAHE (8 x 8 tiles, clip limit = 0.01) helped to bring the picture to the fore and add local contrast. For the sake of this work, the software experiments were done in Python using Matplotlib on a PC running Windows 11 having an Intel Core i5 processor and 16 GB RAM. The ALL, IDB dataset served as a basis for the evaluation and the metrics PSNR, SNR, MSE, SSIM, MAE, AMBE, UQM, IFC, FSIM, and RFSIM helped to quantify the results.

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6. RESULT AND DISCUSSION

The obtained digital blood smear images were tested to a variety of spatial filters, as well as deliberate added random noise such as Gaussian, salt, and pepper noise. The filters significantly reduced noise, thus enhancing image clarity and quality

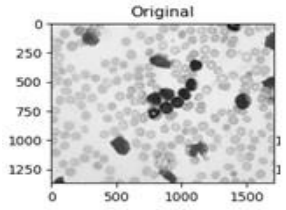
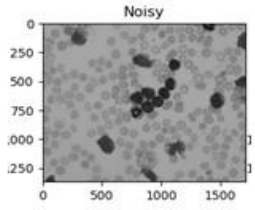
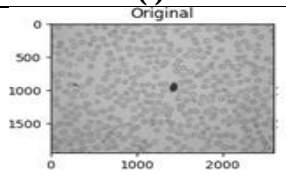
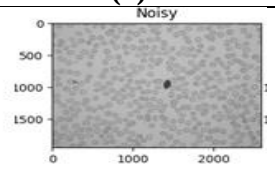
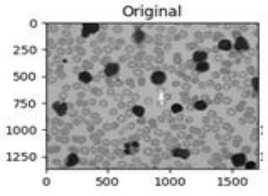
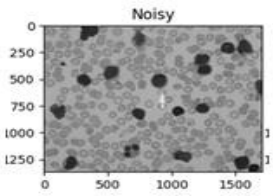
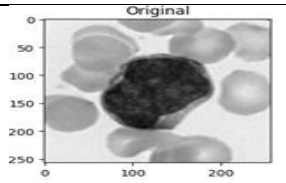
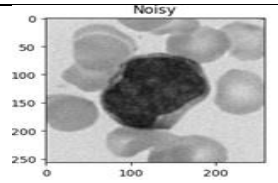
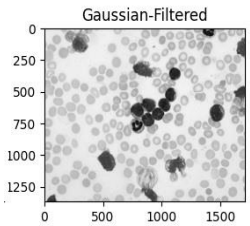
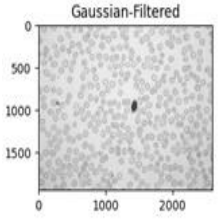
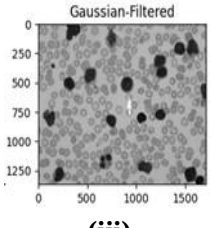
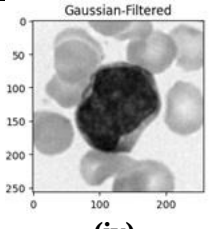
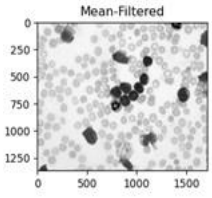
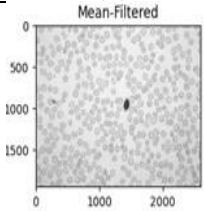
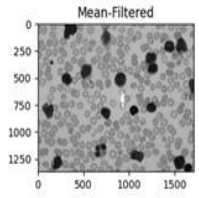
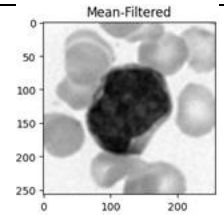
	Original Image	Noisy Image
ALL_ Image	 **(i)**	 **(ii)**
L1_ Image	 **(iii)**	 **(iv)**
L2_ Image	 **(v)**	 **(vi)**
L3_ Image	 **(vii)**	 **(viii)**

Figure. 2 indicates the original images and noisy images of ALL and its Subtypes namely L1, L2 and L3

Filtering Techniques	ALL_Filtered Image	L1_Filtered Image	L2_Filtered Image	L3_Filtered Image
Gaussian	 **(i)**	 **(ii)**	 **(iii)**	 **(iv)**
Mean	 **(v)**	 **(vi)**	 **(vii)**	 **(viii)**

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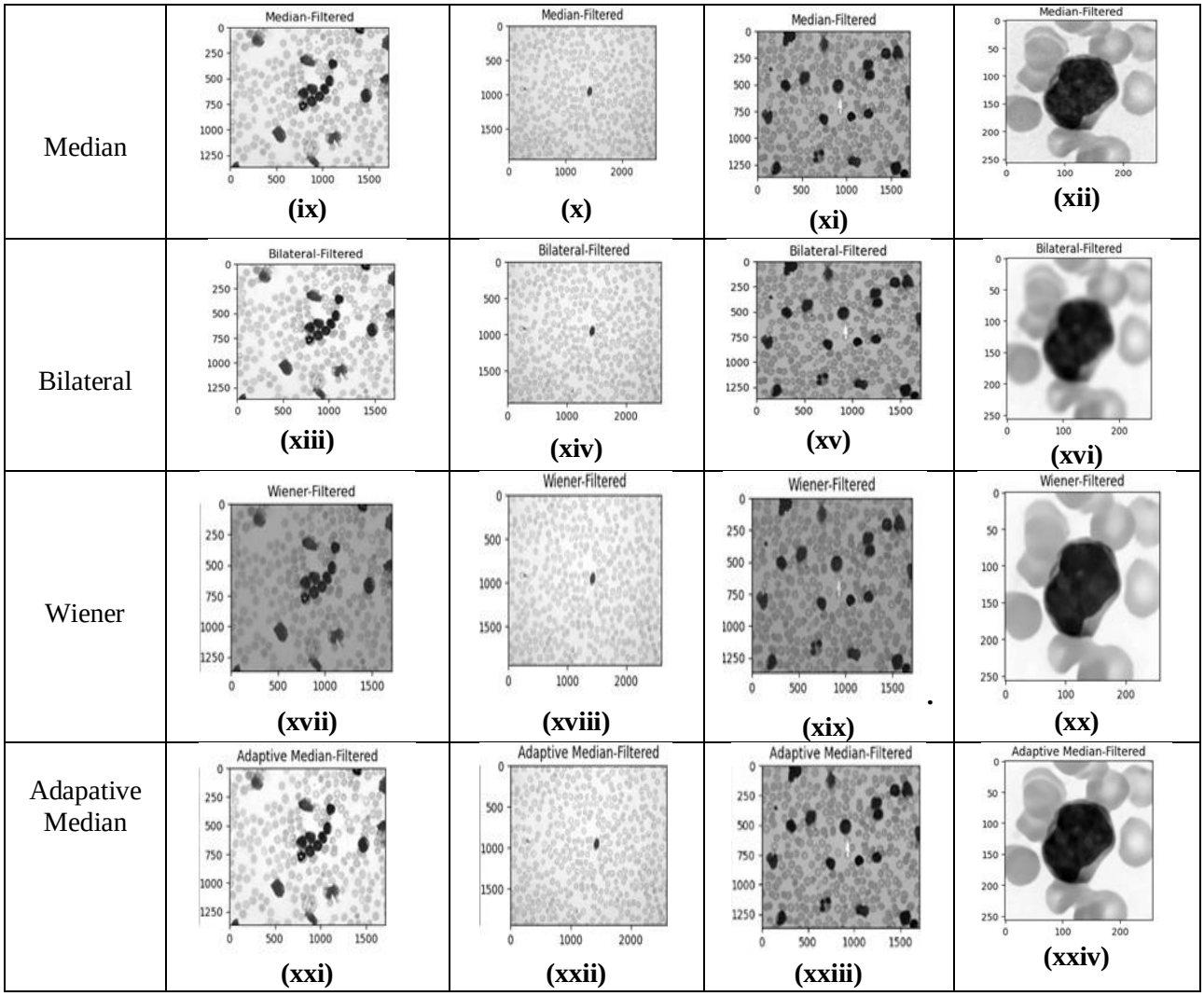

Figure. 3. Indicates the filter images outcomes using Gaussian filter, Mean filter, Median filter, Bilateral filter, Wiener filter, and Adaptive Median filter of ALL and its subtypes

The analysis shows that Gaussian, Wiener, and mean filters are very useful for reducing noise, but they face difficulties when dealing with significant black spots. Optimal performance of median filters has been found for smaller black spots, but for bigger patches, adaptive median filters are needed for achieving an appropriate balance between noise reduction and edge preservation. Following the completion of image filtering, it is usual to assess the efficacy of the filter by employing quality metrics such as PSNR, SNR, and MSE [36] [37] [38]. By comparing the filtered output image to its nonfiltered original, these quantitative measurements assess image quality and enable researchers to evaluation the functionality of various filters in different noise-affected scenarios. The median filter eliminate the salt and pepper noise by substituting each pixel with the median value of the pixels around it. This method helps retain major morphological characteristics like nuclei boundaries in ALL cells and, therefore, can be used for leukemia image preprocessing. The Mean filter removes noise by changing the value of each pixel to the average of its neighboring pixels. It makes the image smoother, but it also blurs the edges and loses some fine details. In ALL cell images, using this filter may change the appearance of the nucleus edges and the texture of the chromatin, thus causing the segmentation to be less accurate. The Bilateral filter is able to eliminate noise while preserving the crucial edges because it takes into account both the spatial and intensity differences. It keeps intact the boundaries of the nucleus and the fine structural details. Therefore, it is very helpful in maintaining the important morphological features of leukemia cells. The Wiener filter is a noise reduction technique that works locally. It is able to identify and remove noise from different areas of the image depending on the variation in each one of these areas. Consequently, the filter is able to keep the details of the image while the overall clarity is still improved. In images of ALL, the filter helps to keep both the shape and texture of the nucleus, thus facilitating fidelity in the analysis and classification. The Adaptive Median filter is a filter that can get rid of impulse noise by changing the dimension of the window filter depend upon the noise level of the local area. The filter can keep the edges and the finer details intact after the process. Using this method, the structure of a nucleus and cell boundaries that can be observed in leukemia images are

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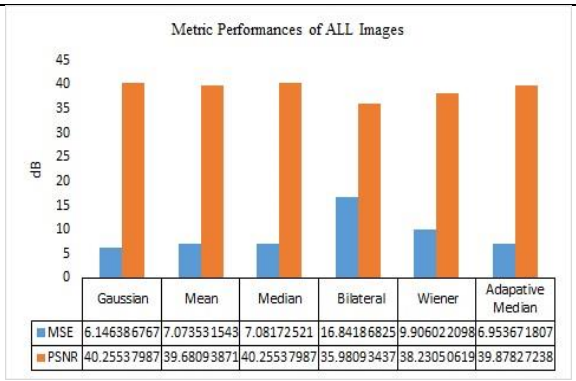
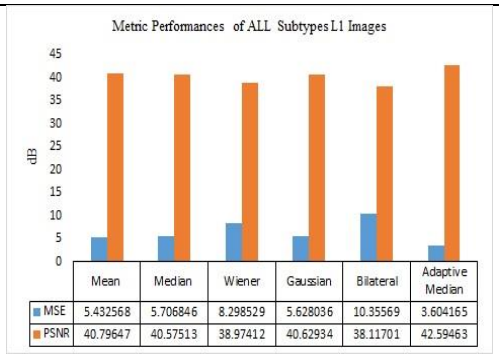
kept the same. The Gaussian filter method for noise reduction works by taking a weighted average of the neighborhood pixels with the weights being determined by a Gaussian distribution. As a result, the image becomes smoother, however, edges and fine details might become less distinguishable. In images of ALL cells, this method can lead to a slight distortion of the nucleus boundaries, which in turn may have an impact on the feature extraction. As shown in the figure 3, Adaptive Median filter is most optimal technique used for noise removal in ALL and its subtypes. Adaptive Median filtered image show reduction in the noise and show visible nucleus boundaries. This enhancement will improves segmentation and helps in accurately overall diagnosing the leukemia.



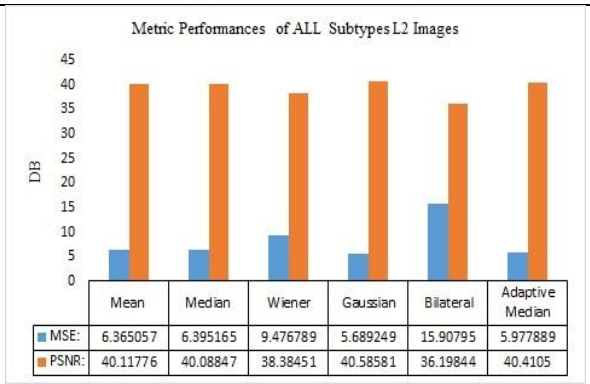
	Gaussian	Mean	Median	Bilateral	Wiener	Adapative Median
MSE	6.146386767	7.073531543	7.08172521	16.84186825	9.906022098	6.953671807
PSNR	40.25537987	39.68093871	40.25537987	35.98093437	38.23050619	39.87827238

Figure. 4. Performance of Spatial Filters of ALL Images



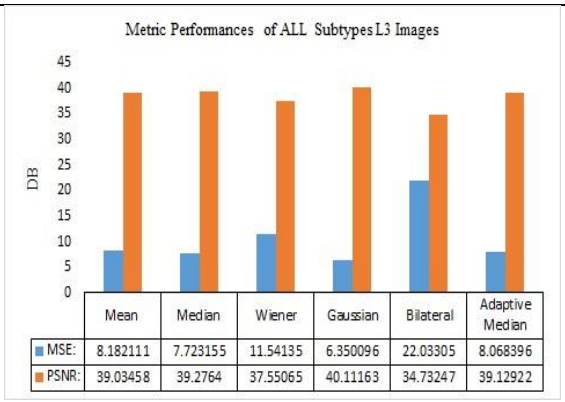
	Mean	Median	Wiener	Gaussian	Bilateral	Adaptive Median
MSE	5.432568	5.706846	8.298529	5.628036	10.35569	3.604165
PSNR	40.79647	40.57513	38.97412	40.62934	38.11701	42.59463

Figure.5. Performance of Spatial Filters of L1 Images



	Mean	Median	Wiener	Gaussian	Bilateral	Adaptive Median
MSE:	6.365057	6.395165	9.476789	5.689249	15.90795	5.977889
PSNR:	40.11776	40.08847	38.38451	40.58581	36.19844	40.4105

Figure.6. Performance of Spatial Filters of L2 Images



	Mean	Median	Wiener	Gaussian	Bilateral	Adaptive Median
MSE:	8.182111	7.723155	11.54135	6.350096	22.03305	8.068396
PSNR:	39.03458	39.2764	37.55065	40.11163	34.73247	39.12922

Figure. 7. Performance of Spatial Filters of L3 Images

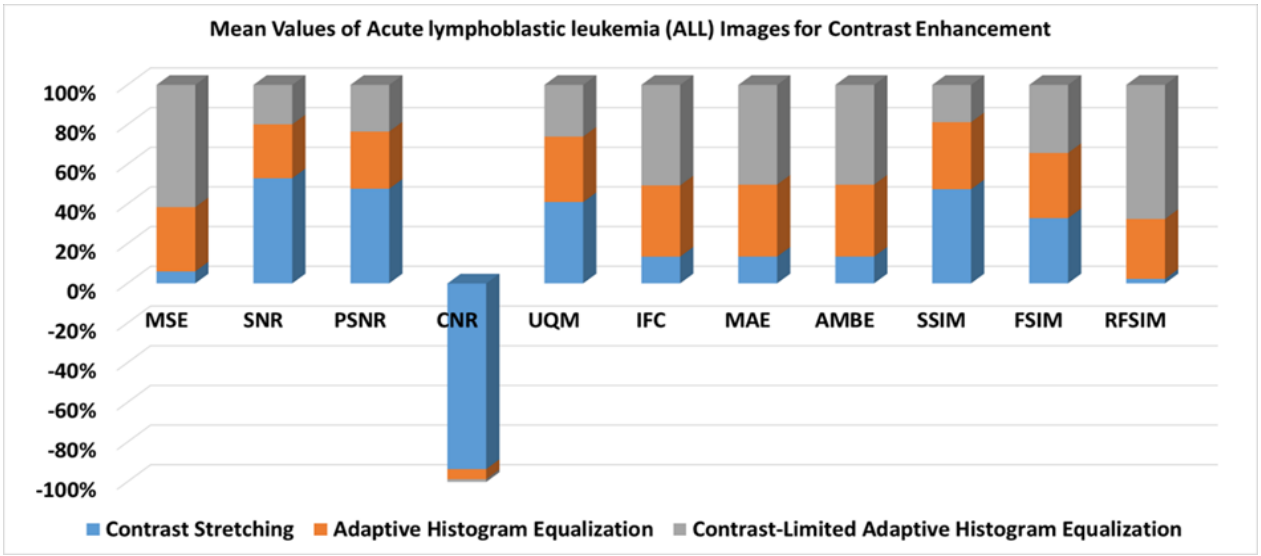


Figure 8: Mean Values of Acute lymphoblastic leukemia (ALL) Images for Contrast Enhancement

Fig.4. to Fig.7. show the performance of several filters applied to acute lymphoblastic leukemia (ALL) images and subtypes. The Gaussian filter consistently provides excellent noise reduction, particularly in ALL subtype images, with the optimal Mean Squared Error (MSE) ratios across all of them. The adaptive median filter

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performs well in noise reduction for subtype L1, whereas the Gaussian filter performs well for subtypes L2 and L3. Fig.4. to Fig.7. Show PSNR is a measure of how well the noise is eliminate from an image, and a higher PSNR refers to a greater image clarity. Nevertheless, a high PSNR alone cannot guarantee the preservation of essential morphological features that are the nucleus shape, size, boundary sharpness, and texture, which are the features to distinguish ALL subtypes (L1, L2, and L3). Median and Adaptive Median filters yield a high PSNR and protect the diagnostic features better at the same time; on the contrary, Gaussian filtering might slightly blur the boundaries. Fig.4. to Fig.8 shows, the combination of Contrast Stretching and the use of the Adaptive Median filter is probably the most appropriate preprocessing method for the intent of enhancement of ALL images.

The aim of the research is to assess different contrast enhancement techniques capable to visually improve, clarify, and provide more diagnostic information from microscopic images of blood smears used in the determination of Acute Lymphoblastic Leukemia (ALL). Since an accurate illustration of the morphological characteristics of the nucleus, such as the shape, size, cytoplasm structure, and chromatin texture, is a basic reliable identification and subtype classification of ALL (L1, L2, and L3), effective image enhancement techniques are essential not only for a correct diagnosis but also for the development of automated This research work mainly discusses three most popular methods used for contrast enhancement: Contrast Stretching (CS), Adaptive Histogram Equalization (AHE), and Contrast Limited Adaptive Histogram Equalization (CLAHE). AHE is one of the methods straightforwardly works to increase image contrast by effectively segmenting an image into smaller areas and then applying histogram equalization to each segment. The local features' visibility is significantly increased, and the fine structural details are also enhanced by the approach. Nevertheless, AHE has the problem that it may cause noise amplification in the homogeneous areas which degrades both the image quality and the faithfulness of the diagnosis. To overcome this drawback, CLAHE is proposed where it sets a limit on how much the image contrast can be enhanced, thus, the noise amplification is reduced while the local contrast is maintained. Although different noise control features of CLAHE over AHE are noticed, there is also a problem that it needs a proper set of parameters and it is computationally more complex. Contrast Stretching is a technique that improves the image contrast by rescaling the intensity values range so that the full dynamic range of the image is used. This technique mainly improves the overall contrast and it does not significantly increase noise nor create artifacts. In comparison to AHE and CLAHE, contrast stretching keeps the general image structure and brightness consistency unchanged, which is especially important in medical imaging where the preservation of the structural integrity is a must.

The experimental analysis was carried out using a publicly accessible Acute Lymphoblastic Leukemia image dataset containing 108 microscopic blood smear images, 49 of which are cancerous and 59 are non, cancerous. The success of the enhancement techniques was judged by the ability of the images to be analyzed by quantitative image quality metrics, including Mean Squared Error (MSE), Signal, to, Noise Ratio (SNR), Peak Signal, to, Noise Ratio (PSNR), Contrast, to, Noise Ratio (CNR), Universal Quality Measurement (UQM), Information Fidelity Criterion (IFC), Mean Absolute Error (MAE), Absolute Mean Brightness Error (AMBE), Structural Similarity Index Measure (SSIM), Feature Similarity Index Measure (FSIM), and Riesz Feature Similarity Index Measure (RFSIM). Each metric looks at a different part of the image quality. The MSE metric finds the mean of the squares of the variation ratio of the pixel values in the original image and the enhanced image. The PSNR and SNR metrics measure the signal-to-noise ratio. Their values are higher when the image is clearer and there is less noise. CNR tells you how much contrast has been increased compared to how much noise has been reduced. This is very important for finding leukemia cells in nearby tissues. SSIM calculates the degree of similarity in the structures of the original and final images, and the nearer the value is to 1, the higher the quality of the image. FSIM and RFSIM evaluate the qualities and morphological characteristics of diagnostic features preserved after enhancement. AMBE judges how well brightness is preserved, so that the enhancement methods do not change the image brightness drastically. UQM offers a thorough quality evaluation by integrating several image quality indices. IFC focuses on how well the visual information that is essential for proper interpretation is retained. Table 1 shows the quantitative comparison of image quality metrics for Contrast Stretching, Adaptive Histogram Equalization, and CLAHE. The outcomes unequivocally indicate that Contrast Stretching is the best performer in terms of multiple key evaluation metrics. Besides the fact that Contrast Stretching recorded the smallest MSE value (0.003938537), which is a sign of less distortion and hence, higher fidelity to the original picture, it also attained the highest SNR (23.14551727), PSNR (28.5283882), UQM (0.988726408), and SSIM (0.984812702) values which are the evidence of its ability to bring out the image details, be less noisy, and maintain the structures of the images. Moreover, Contrast Stretching yielded the lowest MAE (0.046456313) and AMBE (0.046456313) values thus exhibiting better brightness preservation and less enhancement error than AHE and CLAHE. Although CLAHE was able to

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attain higher IFC (0.395812059) and RFSIM (0.371115068) values, which means that it is a better method for the preservation of features, it returned quite big MSE, MAE, and AMBE values, which implies among other things stain brightness deviation and addition of distortion when compared to Contrast Stretching. In the same way, although AHE enhanced the local contrast, it resulted in somewhat higher error and lower structural similarity measures when compared to Contrast Stretching. From the PSNR, SNR, CNR, UQM, and SSIM metrics, it is seen that the Contrast Stretching results have relatively higher values which are an indication of better image quality, the better contrast of enhanced images, and better maintenance of the structure of the images when compared with other methods. Besides that, Contrast Stretching has achieved lower MSE, MAE, and AMBE values which imply that there was less error of enhancement and the brightness was kept better. These traits are cornerstones for medical imaging. Acute Lymphoblastic Leukemia diagnosis is one instance where it is absolutely crucial that morphological features such as nucleus boundaries and structural details be accurately preserved. The visual representation of data in the figures. 4 to 8 and **Table. 2** further attest to the fact that Contrast Stretching perform best in almost all evaluation metrics and subtypes of ALL. Cells boundaries are clearer, contrast is improved, and major structural features are well preserved in images enhanced with Contrast Stretching as compared to those with AHE and CLAHE. From a clinical point of view, it is vital to preserve the morphology of cells in order to be able to figure out the exact subtype of Acute Lymphoblastic Leukemia. Over, enhancement or noise amplification can alter unwanted diagnostic features and hence misleading interpretation. Contrast Stretching is a procedurally sound method for balancing the two aspects, contrast, and structural preservation, and hence it is very appropriate for medical image preprocessing.

Table 2: Comparison of image quality metrics of Acute Lymphoblastic Leukemia Image obtained by different contrast enhancement techniques

Image Quality Metrics (IQM)	Contrast Stretching	Adaptive Histogram Equalization	Contrast-Limited Adaptive Histogram Equalization	Degree
MSE	0.00	0.02	0.04	Lower is better
SNR	23.15	11.87	8.69	Higher is better
PSNR	28.53	17.25	14.07	Higher is better
CNR	-11.52	-0.62	-0.18	Higher is better
UQM	0.99	0.80	0.63	Higher is better
IFC	0.11	0.28	0.40	Higher is better
MAE	0.05	0.12	0.17	Lower is better
AMBE	0.05	0.12	0.17	Lower is better
SSIM	0.98	0.70	0.39	Higher is better
FSIM	0.00	0.00	0.00	Higher is better
RFSIM	0.01	0.17	0.37	Higher is better

Table 3: Quantitative Comparison of Contrast Enhancement and Noise Filtering Techniques for ALL Images

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Category	Method	MSE ↓	PSNR (dB) ↑	SNR (dB) ↑	SSIM ↑	MAE ↓	AMBE ↓	UQM ↑	IFC ↑	RFSIM ↑	Performance Summary
Contrast Enhancement	Contrast Stretching	**0.00**	**28.53**	**23.15**	**0.98**	**0.05**	**0.05**	**0.99**	0.11	0.01	Best overall performance
Contrast Enhancement	AHE	0.02	17.25	11.87	0.70	0.12	0.12	0.80	0.28	0.17	Moderate performance
Contrast Enhancement	CLAHE	0.04	14.07	8.69	0.39	0.17	0.17	0.63	**0.40**	**0.37**	Good feature preservation
Noise Filter	Median Filter	**Low**	High (~38–40)	High	**High**	Low	Low	High	Moderate	High	Best for preserving edges
Noise Filter	Gaussian Filter	Low	**Highest (~39–41)**	**Highest**	Moderate	Moderate	Moderate	High	Moderate	Moderate	Best noise reduction but slight blurring
Noise Filter	Wiener Filter	Moderate	High (~37–39)	High	High	Moderate	Moderate	High	High	High	Good adaptive noise removal
Noise Filter	Mean Filter	Higher	Moderate (~36–38)	Moderate	Lower	Higher	Higher	Moderate	Lower	Lower	Causes blurring
Noise Filter	Bilateral Filter	Low	High (~38–40)	High	**Very High**	Low	Low	High	High	High	Best balance of noise removal and edge preservation
Noise Filter	Adaptive Median Filter	**Lowest**	High (~39–41)	High	**Highest**	**Lowest**	**Lowest**	High	High	High	Best overall noise filter

Table 3 shows the quantitative comparison of contrast enhancement techniques and noise filtering methods that were applied to Acute Lymphoblastic Leukemia microscopic images. Contrast Stretching among the contrast enhancement methods was able to deliver the best performance regarding MSE, MAE, and AMBE values being the lowest, thus indicating very little enhancement error and excellent brightness preservation. Besides that, the method also obtained the maximum PSNR, SNR, UQM, and SSIM values, which means that it is superior in terms of image quality, contrast improvement, and structural preservation. With regard to the noise filtering techniques, the Gaussian filter was top regarding PSNR and SNR values, thus it can be interpreted as having a very strong noise reduction capability. Unfortunately, the method led to blurring of leukemia cell boundaries to some extent, which may have an impact on the morphological analysis. Median and Adaptive Median filters were able to perfectly preserve edges while simultaneously eliminating noise that is crucial for maintaining such diagnostic features as the shape and size of the nucleus. In general, Contrast Stretching along with Adaptive Median or Median filtering has been shown to be the best combination of enhancement and noise removal technique regarding analysis of Acute Lymphoblastic Leukemia image. It helps to achieve better image clarity as well as the preservation of essential morphological features for diagnostics. On the other hand, the bilateral filter was able to accomplish successfully an effective balance among noise elimination and structural preservation.

4. CONCLUSION

The experimental study relied on evaluating different methods of contrast enhancement and noise filtering in order to enhance the diagnostic quality of Acute Lymphoblastic Leukemia (ALL) microscopic images. In a clinical setting, too much smoothing could eliminate some key morphological features necessary for detection and determination of Acute Lymphoblastic Leukemia (ALL). Hence, the choice of filters should be a trade, off between reducing noise and preserving diagnostic features so that an incorrect clinical interpretation is not made. First of all, to the different contrast enhancement methods, Contrast Stretching stood out to be the most effective in terms of performance with it achieving higher values of PSNR, SNR, UQM, and SSIM while it also showed lower values of MSE, MAE, and AMBE which is descriptive of better contrast improvement as well as structural preservation. As regards the noise filters, the use of Adaptive Median and Median filters was the best in terms of noise removal while the important morphological features such as nucleus boundaries were still preserved. Although the Gaussian filter resulted in a greater removal of noise, it also caused slight blurring of the crucial diagnostic features. Thus, the combination of Contrast Stretching and the use of the Adaptive Median filter is probably the most appropriate preprocessing method for the intent of enhancement of ALL images. These methods have the potential to increase the prevalence of the characteristics and thus, aid in great

precision of leukemia detection and classification systems that are automated. This study used only 60 ALL images, which is a relatively small dataset. The Adaptive Median filter led to a significant improvement in PSNR and morphological preservation, but the limited sample size might influence the extent to which the findings can be generalized. A larger dataset is essential to verify its dependability for practical clinical use.

5. RECOMMENDATIONS AND FUTURE WORK

A. Recommendations Section

Contrast Stretching and Adaptive Median filters should be used in ALL image enhancements in general as one of the benefits is that they make the images pop visually and at the same time they retain important morphological features such as nucleus shape, cell boundaries, and chromatin texture. Contrast Stretching works to increase the difference in intensity thereby making the cellular structures more visible and clear without changing or distorting them.

B. Future Work

Future works will encompass more extensive datasets, the incorporation of deep learning techniques, and comprehensive slide image analysis to improve the accuracy, adaptability, and accuracy of Acute Lymphoblastic Leukemia (ALL) detection system

Recommendations

The Adaptive Median filter has been recommended from the experiment results to be the most effective in removing Salt, and, Pepper noise while at the same time preserving the important morphological features such as the nucleus shape, size, and boundaries. The Gaussian filter is suitable for reduction the Gaussian noise; however, there might be a slight loss of structural details due to blurring. Contrast Stretching is recommended for contrast enhancement, as it not only provides clearer images but also preserves the structure better than AHE and CLAHE. For ALL subtype images (L1, L2, and L3), it has been found that the combination of Contrast Stretching and Adaptive Median filtering is the most trustworthy preprocessing method that leads to precise leukemia detection and hence, it facilitates analysis.

Acknowledgement

The authors are grateful to Professor Scotti for providing the dataset of ALL and allowing the used for research purposes. Furthermore, the authors acknowledge the support of their institution and are very thankful to Dr. Ashwini Jogade, Medical Superintendent, Nanavati Max Super Specialty Hospital, Mumbai, for her timely medical expertise and guidance.

Funding Support

The authors declare that no external funding was acquired for this research.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in the ALL-IDB repository at https://homes.di.unimi.it/scotti/all/

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