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Statistical Asymmetrical Histogram Stretching for Contrast Enhancement in Chest X-ray Images for Pneumonia Detection

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Abstract. This paper presents an approach to enhance contrast in chest X-ray images, which improves pneumonia detection when using several convolutional neural networks (CNNs). We introduce a Statistical Asymmetrical Histogram Stretching (SAHS) technique, which addresses the inherent asymmetry in chest X-ray image histograms. Our approach is compared with conventional techniques, like HE, HS and CLAHE, across various CNN architectures including AlexNet, Compact, Enhanced, ResNet-18, MobileNetV2, and ResNet-50. The SAHS method, combined with a Lung Finder Algorithm (LFA), significantly improved classification accuracy across all tested CNN models. SAHS consistently outperformed the conventional methods evaluated (HE, HS, CLAHE), demonstrating its effectiveness, particularly in preserving diagnostically relevant bright regions often altered by other techniques. Therefore, our results demonstrate SAHS is a valuable preprocessing technique for enhancing pneumonia recognition from chest X-ray images.

Keywords. Pneumonia detection, medical image normalization, CNNs, contrast enhancement in medical images, histogram stretching.

1 Introduction

Pneumonia is a severe respiratory disease that can be caused by various pathogens, including viruses, bacteria, and fungi. Its accurate diagnosis based on chest radiographic images is crucial in the medical field, especially in high-demand situations such as pandemics [1]. However, variability in the contrast of these images can significantly affect detection accuracy, potentially leading to misclassifications, as observed in previous studies [2, 3]. The detection of pneumonia in chest X-rays largely depends on identifying characteristic cloudy areas, known as opacities or infiltrates [4]. Nevertheless, the quality and contrast of these images can vary considerably, posing a significant challenge for existing image processing methods [5, 6].

This variability is further intensified in available image datasets, where a lack of uniformity in the alignment and brightness of the region of interest (the lungs) is evident [2]. Effective preprocessing techniques tailored to these characteristics are crucial for improving the performance of deep learning models in medical image analysis [7, 8].

Contrast enhancement in medical images has been an active research area for decades, with a continuous evolution of techniques and methods. Histogram Equalization (HE) has been a fundamental technique, serving as the basis for many subsequent developments [5, 9]. There were conducted a comparative study of various histogram equalization techniques, revealing that while HE improves global contrast, it can introduce artifacts.

[10] expanded this study by evaluating more advanced techniques such as Contrast-Limited Adaptive Histogram Equalization (CLAHE) and Quadrant Dynamic Histogram Equalization

Table 1. Studies performing pneumonia detection in chest radiographs using CNN

Author	Image Preprocessing	CNN Architecture	Accuracy (%)
[21]	None	VGG16, ResNet, Custom CNN	87.5%
[22]	None	Custom CNN	89%
[23]	DWT, Bilateral Filter	Custom CNN	96%
[24]	Normalization, Gamma Correction, CLAHE	ResNet152V2	94.14%

(QDHE). However, these methods present limitations when applied to chest radiographic images [11]. CLAHE, for instance, being a local equalization method, tends to homogenize and enhance contrast in areas where it should not, potentially destroying crucial information related to the smoothness of the cloudy areas indicative of pneumonia [11 ,12]. Additionally, it may introduce noise into the background regions of the image, further complicating the diagnostic process [11]. Alongside equalization, Histogram Stretching (HS) methods aim to enhance contrast by expanding the image's intensity range using various schemes [13, 14, 15, 16]. However, similar to HE, standard HS approaches often assume histogram symmetry or use global statistics that may not be optimal for the specific distributions found in chest radiographs. Another important aspect to consider is the asymmetric nature of histograms in chest radiographic images [17].

This characteristic, coupled with inherent variability in image acquisition, presents significant challenges for automated analysis [18, 19]. This suggests that methods based on symmetric standard deviation may not be optimal for this type of image. In this context, we propose a method to enhance contrast in chest radiographic images, specifically designed to address the discussed challenges.

Our approach is based on an asymmetric histogram expansion, utilizing different standard deviations for gray values greater and smaller than the mean. This method aims to improve contrast more effectively than existing techniques while preserving important information for pneumonia diagnosis. To evaluate the effectiveness of our contrast enhancement method, we employed a variety of convolutional neural network (CNN) architectures for chest radiographic image classification. The architectures used include MobileNetV2, ResNet-50, ResNet-18, Compact, Enhanced, and AlexNet, all available on the MVTEC Deep Learning Tool platform [20]. The primary objective is to assess how different contrast enhancement techniques affect the classification accuracy of chest X-rays using these various CNN models. This approach allows us not only to compare the efficacy of preprocessing techniques but also to analyze their interaction with different neural network architectures.

This paper is organized into four main sections. Section 2 provides a detailed analysis of the asymmetric histograms characteristic of chest radiographic images and explains our proposed method for asymmetric histogram contrast enhancement and lung region normalization. Next, Section 3 describes the experiments conducted to evaluate the method's effectiveness, comparing our approach’s performance with conventional contrast adjustment techniques. Finally, Section 4 presents the conclusions of this study.

2 Experimental Procedures

This section analyzes the asymmetric histograms characteristic of chest radiographs and proposes a contrast enhancement technique based on this asymmetry.

2.1 Preprocessing in Pneumonia Detection

Table 1 provides an overview of the most recent approaches in chest radiograph classification, highlighting the variety of preprocessing techniques and CNN architectures used. This comparison demonstrates the benefit of using preprocessing techniques such as contrast

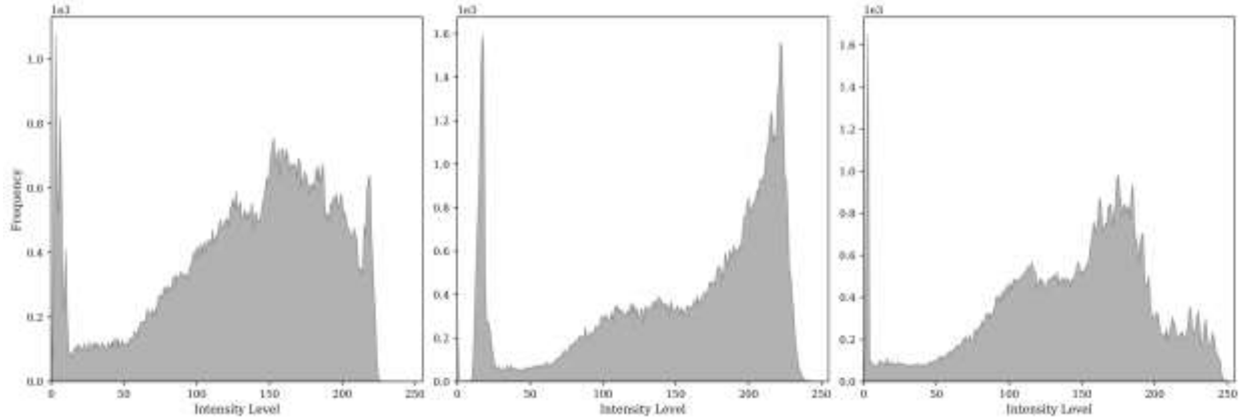

Fig. 1. Visualization of the characteristic histogram shape in different chest radiographic images

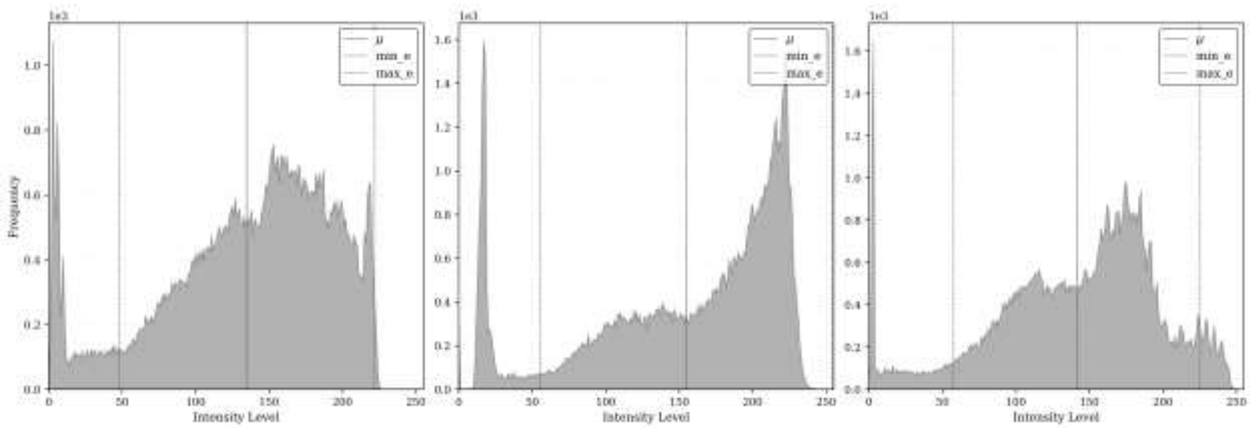

Fig. 2. Illustration in different images of the statistical maximum and minimum, it can be observed that, when using these limits based on 1.5 times the standard deviation, the representation of the range of intensities is improved, this shows that if we use the common deviation it may be fine towards the top of the standard deviation, but conflicts are found below the standard deviation, therefore an asymmetric deviation should be used and thus be able to obtain the maximum and statistical minima that best suit what is needed

enhancement, which improve accuracy in pneumonia detection.

2.2 Characteristics of Histograms in Chest Radiographic Images

Chest radiographic images typically exhibit a non-uniform intensity distribution, with a tendency towards darker tones due to the presence of air-filled lung regions [6]. This characteristic results in histograms that are noticeably asymmetric, with a distinctive shape [11], as shown in Figure 1. The histogram features a narrow peak on the far left, followed by a long, low-amplitude region that gradually increases to a prominent maximum on the right.

2.3 Effects of Different Contrast Adjustment Methods on Classification

Histogram Equalization (HE). While effective for normalizing an image dataset, HE balances pixel quantities across all gray levels, which may negatively impact classification. Specifically, in lung images, pneumonia cases exhibit more bright regions within the lungs compared to normal cases, and HE may alter this balance.

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Fig. 3. Comparison of contrast enhancement methods: (a) Original image, (b) Result of Histogram Stretching using absolute min/max limits, (c) Result of Histogram Stretching using statistical limits based on standard deviation (Section 2.4)

Local Histogram Equalization (CLAHE: Contrast-Limited Adaptive Histogram Equalization). Although useful for correcting varying contrasts in different image regions, CLAHE presents the same classification issue as HE. Additionally, it amplifies noise in smooth areas, potentially causing false infection-like artifacts and reducing classification accuracy. CLAHE introduces significant limitations [11], including the destruction of subtle classification-relevant information and the addition of artifacts unrelated to distinguishing pneumonia from normal cases.

While both HE and CLAHE are foundational techniques, their detailed formulations are well-established in standard image processing literature. Given the scope of this paper and the focus on addressing histogram asymmetry, we provide a more in-depth analysis of the Histogram Stretching (HS) variants in the subsequent sections [15, 16].

Histogram Stretching (HS). HS maintains the proportion of bright and dark regions, but its reliance on global minimum and maximum values can be problematic when outlier pixels are present. A more robust approach involves calculating an average minimum and maximum based on standard deviation. However, given the asymmetric nature of these histograms (Figure 1), using a symmetrical standard deviation approach can be ineffective, as it may set inappropriate limits (Figure 2) quantities across all gray levels, which may negatively impact classification. Specifically, in lung images, pneumonia cases exhibit more bright regions within the lungs compared to normal cases, and HE may alter this balance.

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2.4 Contrast Adjustment by Statistical Histogram Stretching

Unlike min–max normalization methods that rely on the absolute extreme intensity values, defining stretching limits based on statistical measures is a more robust approach, particularly for images with outliers. Various histogram modification and

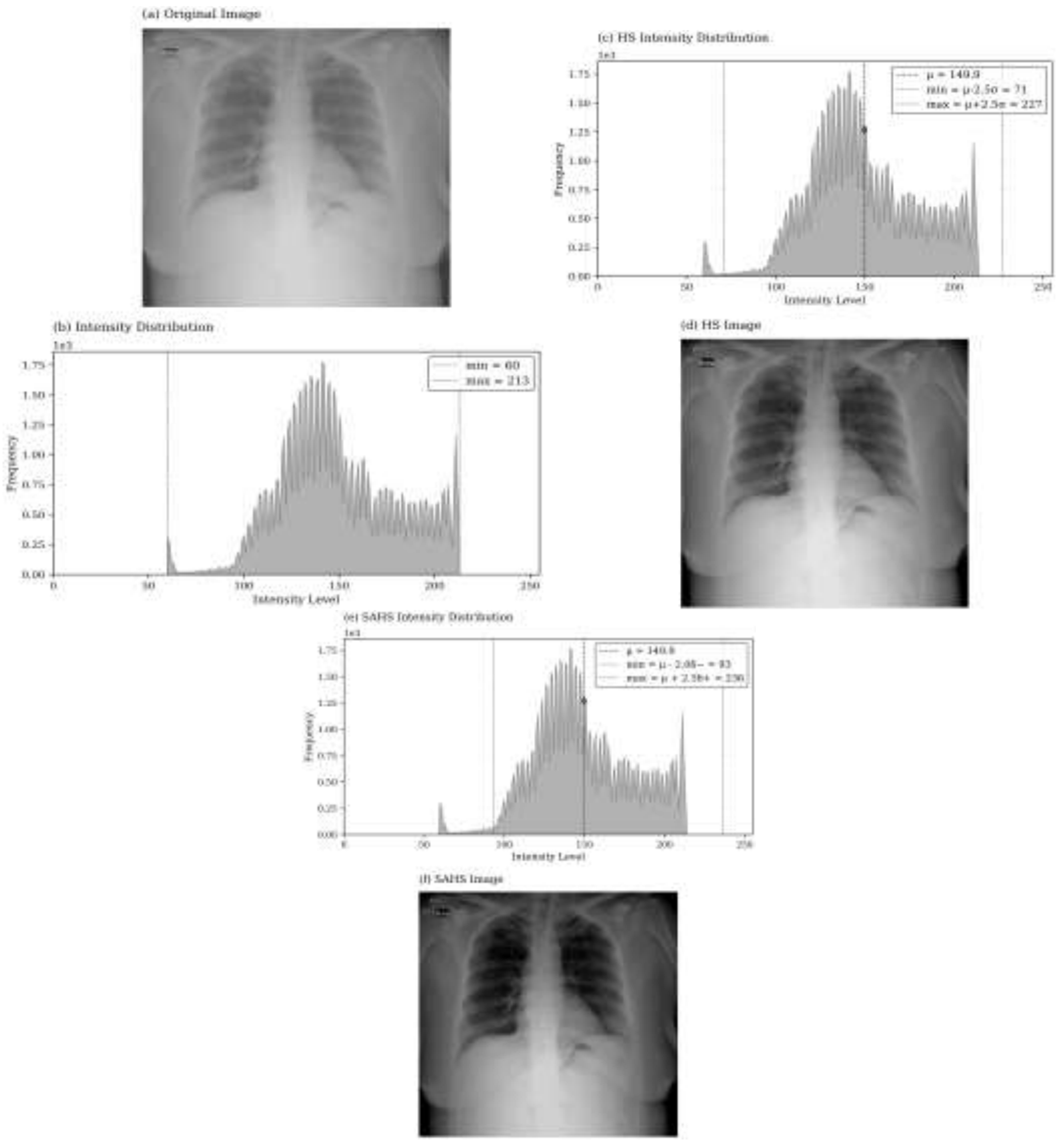

Fig. 4. Comparison of the original X-ray image, Histogram Stretching (HS), and Statistical Adaptive Histogram Stretching (SAHS) techniques. The first column presents the original image (a) and its corresponding intensity distribution (b). The second column shows the results of HS, including its adjusted intensity histogram (c) and the enhanced image (d). The third column displays the SAHS approach, with its modified intensity distribution (e) and the resulting enhanced image (f). The SAHS method demonstrates improved contrast adaptation, particularly in the presence of asymmetrical histograms, by adjusting intensity limits based on statistical measures

stretching techniques exist, aiming to improve contrast while preserving image characteristics [13, 14]. In chest radiographic images, the presence of outlier pixels, often due to noise or artifacts, can skew the overall intensity range if simple min-max is used. Using statistical limits helps mitigate this, a concept discussed in earlier works [6, 11] and classical texts [15, 16].

This implementation defines these limits statistically as follows.

Let $I(x,y)$ denote the pixel intensity at position (x,y) in an image of dimensions $n \times m$, with $N = n \times$

Fig. 5. Visual comparison of Original, CLAHE, and SAHS processing on three different chest X-ray examples (left to right panels in each triplet). Note how CLAHE can amplify noise or darken bright regions compared to SAHS

m being the total number of pixels. The mean intensity, μ, is computed as:

$$\mu = \frac{1}{N} \sum_{x=1}^{n} \sum_{y=1}^{m} I(x,y), \quad (1)$$

and the standard deviation, σ, is given by:

$$\sigma = \sqrt{\frac{1}{N} \sum_{x=1}^{n} \sum_{y=1}^{m} (I(x,y) - \mu)^2}. \quad (2)$$

Rather than using the absolute extreme intensity values determined through min–max normalization, the lower and upper bounds are defined as follows:

$$I_{min} = \mu - k * \sigma, \quad (3)$$

$$I_{max} = \mu + k * \sigma. \quad (4)$$

This adjustment ensures that the selected range covers most pixels, excluding those extreme values that could correspond to noise or artifacts. In our implementation, we set k = 2.5.

The mapping function for transforming the image to an 8-bit scale is then expressed as:

$$\mathrm{I}'(\mathrm{x},\mathrm{y}) = 255 \cdot \frac{\mathrm{I(x,y) - I\_min}}{\mathrm{I\_max - I\_min}}. \quad (5)$$

with a clipping operation ensuring that the resulting values remain within the [0, 255] interval.

This statistical method minimizes the influence of spurious pixels and preserves the relevant intensity variations. As demonstrated in our experiments as seen in Figure 3 and supported by findings in [9] this approach not only provides a more representative dynamic range but also enhances the performance of subsequent classification tasks by maintaining the critical contrast necessary for accurate pneumonia detection.

In summary, the contrast adjustment by histogram stretching in situations where the presence of spurious pixels is a problem, the use of absolute min and max limits are inadequate; however, a statistical approach guarantees a consistent improvement in contrast even in the presence of these anomalies, offering a more reliable solution for the preprocessing of radiographic images.

However, while this statistical HS method effectively handles outliers better than absolute min-max stretching, it inherently fails to address the asymmetry common in chest X-ray histograms (Figure 1). Using a single standard deviation σ symmetrically around the mean μ often leads to suboptimal limits for these skewed distributions. This limitation directly motivates the need for an asymmetric approach, which we introduce in the following section as the SAHS method.

2.5 Contrast Adjustment by Histogram Expansion Based on Asymmetry (SAHS)

This article proposes the Statistical Asymmetrical Histogram Stretching (SAHS) contrast enhancement method, which calculates two distinct deviations for gray values above and below the histogram mean, μ (defined in Equation (1)).

Considering the input grayscale image *I(x,y)* of size *n x m* and its mean intensity μ, we first perform gray level separation:

$A = \{values\ of\ I(x,y) \mid I(x,y) > \mu\}$ (values above the mean), (6)

$B = \{values\ of\ I(x,y) \mid I(x,y) \leq \mu\}$ (values below or equal to the mean). (7)

Calculation of expansion limits:
Upper limit:

$$u = \mu + 2.5\, \partial_{+}. \quad (8)$$

.Lower limit:

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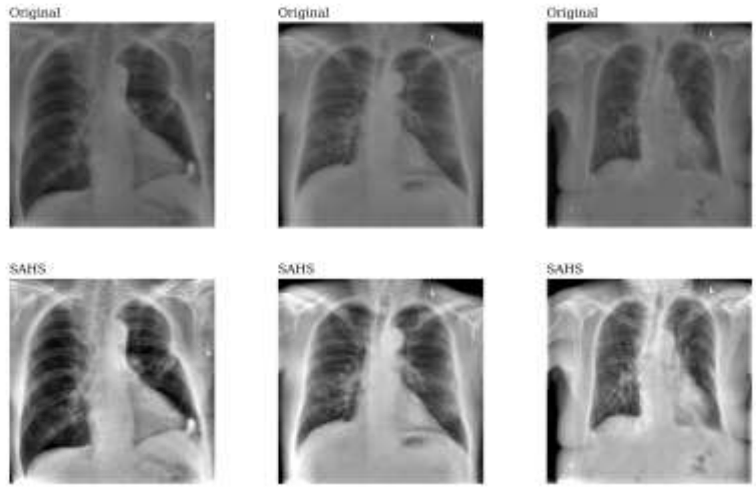

Fig. 6. Comparison of radiographic chest images with pneumonia before and after applying SAHS

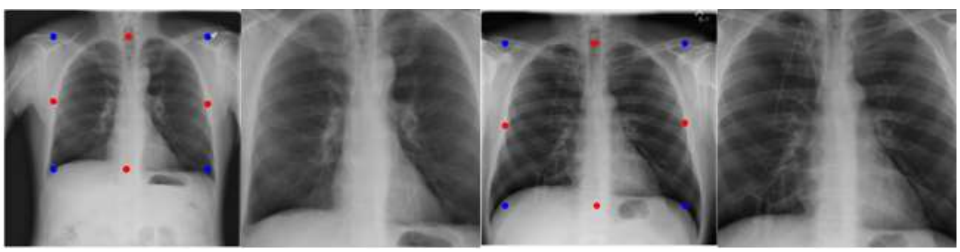

Fig. 7. Lung Localization Algorithm (ALP) process examples on SAHS-processed images. Red points indicate predicted landmarks (Q1-Q4), blue points define the bounding box for ROI extraction: (a) Example 1, (b) Example 2

$$l = \mu - 2.0\,\partial_- \,. \tag{9}$$

The constants 2.5 and 2.0 are empirically derived values. We observed that these values provided a better fit to the histograms across the entire training dataset.

Where ∂_+ and ∂_- are the average deviations of *A* and *B* with respect to the overall mean μ:

$$\partial_+ = \sqrt{\frac{1}{\#A}\sum_{\forall a \in A}(I(x,y)-\mu)^2}\,. \tag{10}$$

$$\partial_- = \sqrt{\frac{1}{\#B}\sum_{\forall b \in B}(I(x,y)-\mu)^2}\,. \tag{11}$$

Using *u* and *l* as the maximum and minimum gray levels found in the image *I(x,y)*, we can establish a mapping function:

$$I'(x,y) = 255 \cdot \frac{I(x,y)-l}{u-l}, \tag{12}$$

where *I'(x,y)* would be the contrast-corrected image. On the other hand, in practice, it would be forced by a clipping function to make the values of *I'(x,y)* be 8-bit unsigned integers (0 – 255), and those that are greater than 255 would be equal to 255, while negative values would be equal to 0.

Below is an unprocessed image containing extreme, yet infrequent, intensity values, with the asymmetry in its histogram being representative of radiographic images. Adjacent to it is a processed image, which has undergone processing using the statistical stretching method and then the SAHS method. Figure 4 shows that the proposed method SAHS does a better job when working with highly asymmetric histograms when compared with the statistical histogram stretching approach.

This method, in addition to being computationally lighter than CLAHE, offers

Fig. 8. Stages of the integrated preprocessing pipeline: (a) Original chest X-ray image, (b) Image after applying SAHS contrast enhancement, (c) Extracted Region of Interest (ROI) after applying ALP

advantages for the specific case of the type of asymmetric histogram typical in this class of radiographic chest images. Figure 3 shows that CLAHE emphasizes noise in an X-ray without pneumonia, making it appear that there could be lesions (second trio of images). In the third trio of the same Figure 5, it is illustrated that the light regions of an image with pneumonia could be darkened by CLAHE, not being so when SAHS is used. Finally, Figure 6 shows the SAHS contrast adjustment for 3 different images.

Lung Localization Algorithm (ALP)

To improve classification accuracy, we used the Lung Localization Algorithm (ALP) proposed in [25, 26], which allows extracting or segmenting the pulmonary region of interest (ROI) in radiographs.

The ALP uses K-NN regression to estimate the coordinates of the ROI in a new radiograph image test.

The ALP process is summarized in the following steps:

– Landmark Identification: Four key points (Q1, Q2, Q3, Q4) are defined that delimit the pulmonary region.
– K-NN Regression: The coordinates of these points are predicted in the test image.
– Warping: A geometric transformation is applied to extract the ROI and normalize it to a 256x256 pixel image.

This approach ensures that all processed images have the same alignment, which improves classification [25,26].

2.6 Integration of SAHS and ALP Methods

The combination of SAHS with ALP provides robust preprocessing for radiographic chest images:

– Initial contrast enhancement: The asymmetric histogram expansion method is applied to the original image.
– Lung localization: ALP is used to extract and normalize the ROI.

This process is illustrated in Figure 8.

In the following sections, the experimental results will be presented demonstrating the effectiveness of this method compared to conventional contrast enhancement techniques, using various CNN architectures for the classification of chest radiographic images.

3 Results

To evaluate the effectiveness of SAHS (Statistical Asymmetrical Histogram Stretching) compared to conventional techniques, we conducted a series of experiments using various convolutional neural network (CNN) architectures for chest radiograph classification. The results were compared with the

Table 2. Accuracy results (hit rate) of the experiments

CNN Model	HE	CLAHE	HS	SAHS
AlexNet	89.4%	91.6%	90.6%	92.8%
Compact	92.1%	91.6%	92.8%	93.8%
Enhanced	93.1%	93.6%	94.6%	95.1%
ResNet-18	93.8%	92.1%	95.6%	96.3%
MobileNetV2	95.6%	96.0%	94.8%	95.1%
ResNet-50	93.6%	95.3%	95.6%	95.8%

performance of the same architecture using HE, HS and CLAHE.

3.1 Setup

A dataset of 2,700 chest X-ray images was used, consisting of 1,350 images from healthy patients and 1,350 from patients with pneumonia, which were used to train and test the CNN models. These images are separated at source at the time of download, which implies that both classes could have different conditions inherent to their original source. Therefore, contrast adjustment is required to ensure that both normal and pneumonia images are under the same brightness and contrast conditions. These images were taken from the COVID-19_Radiography_Dataset on Kaggle [27]. All images were resized to 256×256 pixels before applying contrast enhancement and the ALP method. The inherent variability in acquisition conditions across datasets further motivates the need for contrast normalization techniques like those evaluated here. We used six different CNN architectures: AlexNet, Compact, Enhanced, ResNet-18, MobileNetV2, and ResNet-50, all available on the MVTEC Deep Learning Tool platform [20]. The dataset (2700 images total) was split into training (70%, 1890 images), validation (15%, 405 images), and test sets (15%, 405 images) using a fixed random seed (1) for reproducibility. Models were trained on the training set for 100 epochs using the ADAM optimizer with a learning rate of 1×10^{-4} and a batch size of 32. Input images were treated as single channel (grayscale). To assess robustness and tune parameters during development, 5-fold cross-validation was used to evaluate the models' performance. The final accuracy results reported in Table 2 were obtained by evaluating the models on the test set.

3.2 Classification Results

Table 2 Shows the accuracy results obtained for each CNN architecture and preprocessing method.

3.3 Results Analysis

- Superiority of the SAHS method: Our SAHS method outperformed CLAHE in most cases, with notable improvements in AlexNet, Compact, Enhanced, and ResNet-18.
- Efficacy of the HS Method: The HS method offers a consistent accuracy boost over HE, with noticeable gains in simpler models like AlexNet and Compact. While its performance is generally competitive with CLAHE, especially evident in Enhanced and ResNet-18 it remains slightly below SAHS in maximizing accuracy, suggesting its potential as an effective yet balanced preprocessing alternative:
  - Performance by architecture:
  - ResNet-18 showed the greatest improvement with SAHS, reaching 96.3% accuracy.
  - MobileNetV2 and ResNet-50 performed similarly with CLAHE and SAHS, with SAHS having a slight advantage in ResNet-50.
- Consistency: SAHS proved to be more consistent in improving accuracy across different architectures, suggesting better adaptability to various CNN models.
- Effectiveness in simpler architectures: The improvement was more pronounced in simpler architectures like AlexNet and Compact, indicating that SAHS can be especially beneficial when using less complex models.

The consistent advantage of SAHS, particularly over CLAHE and HS, likely stems from its ability to adaptively enhance contrast based on the inherent asymmetry of chest X-ray histograms, potentially preserving subtle diagnostic features better than

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symmetric or locally aggressive methods. While additional performance metrics like precision and recall could offer further insights, they are omitted here due to space constraints.

4 Conclusions

The results demonstrate that SAHS is effective in improving classification accuracy across various CNN architectures, consistently outperforming standard HE and symmetric HS methods, and also surpassing the widely used CLAHE technique in most tested scenarios.

The effectiveness of SAHS can be attributed to its ability to adapt contrast enhancement to the asymmetric nature of histograms in chest radiographic images, preserving critical diagnostic information while improving the visibility of relevant structures. It's important to note that while SAHS showed consistent improvements, the magnitude of improvement varied across different architectures.

This suggests that the choice of preprocessing method should be considered in conjunction with the selection of CNN architecture to optimize the overall classification system performance. The main contributions of this paper are twofold: a contrast adjustment method for asymmetric histograms SAHS such as those present in chest radiographic images, and the successful integration of SAHS with the Lung Locator Algorithm (ALP) for more accurate classification of pneumonia in chest radiographic images. In conclusion, these results support the effectiveness of the proposed SAHS method in this article as a valuable preprocessing technique for improving accuracy in chest radiographic image classification using various CNN architectures.

As future work, we propose analyzing the histogram shape in greater detail to develop even more tailored contrast adjustment methods, potentially using stable regions like the spine for reference. Furthermore, evaluating the SAHS method on additional diverse datasets and testing its impact when combined with other machine learning classifiers beyond CNNs (such as Random Forest or XGBoost) would further validate its generalizability and effectiveness.

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