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Optimized Chest X-Ray Image Processing for Accurate Automated Disease Detection

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Abstract: The role of medical imaging is pivotal in the diagnosis of numerous diseases, particularly respiratory conditions. However, noise artifacts, including salt-and-pepper noise and Gaussian noise, can significantly impair the quality of chest X-ray (CXR) images, potentially resulting in misdiagnoses. This research aims to improve CXR images by employing noise removal techniques followed by histogram equalization to enhance overall image quality. Two datasets are utilized: one from a publicly available source and another collected from laboratory environments. The latter dataset is subjected to a manual noise removal process to ensure superior image clarity. Subsequently, a Convolutional Neural Network (CNN) model, specifically ResNet-50, is applied for classification across both datasets. A comparative analysis is conducted to demonstrate that images that have been manually denoised achieve greater accuracy than those that remain noisy. The results of the experiments substantiate the effectiveness of the proposed approach in enhancing image quality and improving diagnostic accuracy.

Keywords: Chest X-Ray, Image processing, CXR, Salt and Pepper Noise, Gaussian Noise, Respiratory system, Convolutional Neural Network, CNN.

I. INTRODUCTION

Chest X-ray (CXR) imaging serves as a crucial diagnostic instrument for identifying various pulmonary conditions, such as pneumonia, tuberculosis, and COVID-19. Nonetheless, medical images frequently encounter different forms of noise that hinder their interpretability and the accuracy of automated classification systems. Among these, salt-and-pepper noise and Gaussian noise are particularly prevalent. Conventional noise reduction methods, including median filtering and Gaussian smoothing, can mitigate noise but often at the expense of image detail. This research presents a comprehensive strategy for noise elimination in CXR images, the application of histogram equalization to enhance image quality, and the utilization of a deep learning model (ResNet-50) for classification purposes. A comparative analysis between a publicly available dataset and a dataset collected in a laboratory setting underscores the benefits of manual noise removal and preprocessing in enhancing classification accuracy.

II. BACKGROUND STUDY

The exploration of noise reduction and enhancement techniques in medical imaging has garnered significant attention in recent years. Suzuki [1] conducted a review of deep learning applications in medical imaging, highlighting the critical role of noise removal in the detection of diseases. Anwar et al. [2] examined the contributions of convolutional neural networks (CNNs) to the advancement of medical image analysis. Traditional denoising techniques, such as median filtering and wavelet transforms, have been widely implemented, yet their efficacy can vary depending on the intensity of the noise and the type of image. Kang et al. [3] introduced deep learning-based denoising methods, demonstrating superior performance compared to traditional approaches. Likewise, Wang and Zhao [4] investigated CNN-based noise reduction strategies, emphasizing their capacity to maintain essential medical details.

Moreover, Howard et al. [5] introduced adaptive histogram equalization as a method for improving X-ray images, which notably enhances image contrast and diagnostic clarity. Liu et al. [6] established a deep learning framework aimed at classifying lung diseases through enhanced chest X-ray (CXR) images, thereby emphasizing the critical role of image preprocessing. Alshaye et al. [7] presented hybrid filtering methods that integrate various denoising techniques to achieve superior outcomes. Furthermore, Gupta and Singh [8] performed a comparative study of histogram equalization methods, finding that adaptive techniques surpass traditional ones in the context of medical imaging. Collectively, these investigations highlight the essential need for noise reduction and enhancement strategies in

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medical image processing, forming the basis for this research.

III. REMOVING NOISE FROM CHEST X-RAY IMAGES

Chest X-ray images are affected by two primary types of noise, which can compromise classification accuracy:

a. Salt and Pepper Noise
b. Gaussian Noise

a) Salt and Pepper Noise

Salt and pepper noise is a prevalent form of distortion in digital images, characterized by the sporadic appearance of white (salt) and black (pepper) pixels. This type of noise typically arises from transmission errors, dust interference, or malfunctions in imaging sensors. It manifests as abrupt changes in intensity, resulting in a grainy and distorted visual quality.

Algorithm: Remove_Salt_Pepper_Noise

Input: Noisy Image

Output: Denoised Image

Procedure:

1. Load the input image.

2. Specify the size of the filter window (e.g., 3×3).

3. For each pixel (excluding the borders):

a. Gather the neighboring pixels within the defined filter window.
b. Sort the pixel values.
c. Substitute the current pixel with the median value from the sorted array.

4. Save the filtered image.

5. Return the denoised image.

b) Gaussian Noise

Gaussian noise is a type of statistical noise that adheres to a normal distribution (bell curve) and is frequently introduced into images due to sensor inaccuracies, low illumination, or interference from electronic circuits. This noise is characterized by random fluctuations in pixel intensity, which can render images blurry or grainy.

Algorithm: Remove_Gaussian_Noise

Input: Noisy Image

Output: Denoised Image

Procedure:

1. Load the input image.

2. Define a Gaussian kernel (e.g., 3×3) with a specified standard deviation (σ).

3. For each pixel in the image:

a. Collect the neighboring pixels within the kernel window.
b. Calculate the weighted sum using the Gaussian kernel.
c. Update the pixel with the computed value.

4. Save the filtered image.

5. Return the denoised image.

IV. HISTOGRAM EQUALIZATION

Histogram Equalization is a method employed to enhance the contrast of an image by redistributing its intensity values. The following is a detailed, step-by-step guide using a 3-bit image (with intensity levels ranging from 0 to 7) consisting of 20 pixels:

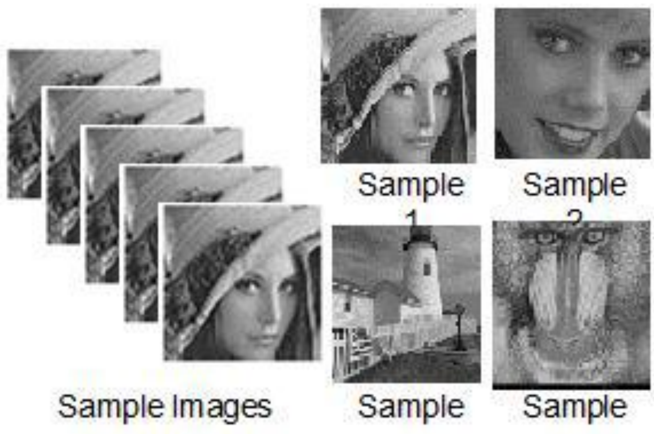

Figure 1: Sample Input Images from standard medical image Dataset

Step 1: Define the Pixel Intensity Distribution

Begin by examining the grayscale intensity values present in the image along with their respective pixel counts. The total

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number of pixels is 20.

Step 2: Compute the Probability Density Function (PDF)

The PDF is determined by dividing each pixel count by the total number of pixels:

Count Pixels PDF(i) = Total Pixels / Pixel Count(i)

Step 3: Compute the Cumulative Distribution Function (CDF)

The CDF is derived as follows:

$$CDF(i) = CDF(i-1) + PDF(i)$$

Step 4: Compute the Equalized Intensity Values

The new intensity values are calculated using the formula:

New Intensity = Round(CDF(i) × (Max Intensity = 7))

Step 5: Replace the Old Intensities

Substitute each original intensity in the image with its corresponding new intensity:

Pixels with intensity 0 → 1
Pixels with intensity 1 → 2
Pixels with intensity 2 → 3
Pixels with intensity 3 → 4
Pixels with intensity 4 → 5
Pixels with intensity 5 → 6
Pixels with intensity 6 → 7
Pixels with intensity 7 → 7

As a result, the image exhibits improved contrast with intensity values that are more uniformly distributed.

V. EXPERIMENTAL RESULTS

Two datasets, designated as X1 and X2, were utilized in this study. The first dataset, X1, was sourced from the public domain and consists exclusively of chest X-ray images, categorized into two labels: normal and abnormal.

Figure 2: Comparison of various parameters related to the existing and proposed method

The second dataset, X2, was obtained directly from laboratories. In the preprocessing phase, two types of noise—salt and pepper noise, as well as Gaussian noise—were eliminated from the dataset, followed by the application of Histogram Equalization. Both datasets contain an equal number of chest X-ray images. The ResNet50 model was trained independently on each dataset, and the resulting accuracy was documented. The details of the accuracy are presented in the following table.

VI. CONCLUSION

This research highlighted the efficacy of noise reduction and histogram equalization techniques in enhancing the quality of chest X-ray images for medical diagnostic purposes. A comparative analysis between a public domain dataset and a manually refined dataset revealed a notable increase in classification accuracy when employing the ResNet-50 model. The accuracy achieved with the public dataset was 88.34%, while the enhanced dataset yielded a superior accuracy of 92.45%. These findings underscore the critical role of preprocessing methods in augmenting the performance of deep learning models. Future research may investigate more sophisticated noise reduction techniques and their effects on various deep learning architectures to further improve medical image classification outcomes.

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