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Improving the Quality of Chest X-Ray images for better Classification using Convolutional Neural Network

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***Abstract*—Medical imaging plays a crucial role in diagnosing various diseases, including respiratory disorders. However, noise artifacts such as salt-and-pepper noise and Gaussian noise significantly degrade the quality of chest X-ray (CXR) images, potentially leading to inaccurate diagnoses. This research focuses on enhancing CXR images by applying noise removal techniques followed by histogram equalization to improve image quality. Two datasets are utilized: one from a public domain and another collected from laboratories. The latter undergoes a manual noise removal process to ensure enhanced image clarity. Subsequently, a Convolutional Neural Network (CNN) model, specifically ResNet-50, is applied to both datasets for classification. Comparative analysis is performed to demonstrate that manually denoised images yield better accuracy than raw noisy images. The experimental results validate the effectiveness of the proposed approach in improving image quality and diagnostic accuracy.**

***Index Terms*—Salt and Pepper Noise, Gaussian Noise, Convolutional Neural Network (CNN)**

I. INTRODUCTION

Chest x-ray (cxr) imaging is one of the most widely used diagnostic tools for detecting lung diseases, including pneumonia, tuberculosis, and covid-19. However, medical images often suffer from various types of noise that affect their interpretability and accuracy in automated classification models. Among these, salt-and-pepper noise and Gaussian noise are predominant. Traditional noise removal techniques, including median filtering and Gaussian smoothing, can reduce noise but often compromise image details. This study proposes a systematic approach to remove noise from CXR images, apply histogram equalization for quality enhancement, and use a deep learning model (ResNet-50) for classification. The comparative evaluation between a public dataset and a lab-collected dataset highlights the advantages of manual noise removal and preprocessing in improving classification accuracy.

II. BACKGROUND STUDY

Noise reduction and enhancement techniques in medical imaging have been extensively studied in recent years. Suzuki [1] reviewed deep learning applications in medical imaging, emphasizing the significance of noise removal in disease detection. Anwar et al. [2] discussed convolutional neural networks (CNNs) and their role in improving medical image analysis. Traditional denoising methods, such as median filtering and wavelet transform, have been used widely, but their effectiveness varies based on noise intensity and image type. Kang et al. [3] introduced deep learning-based denoising techniques, demonstrating improved performance over conventional methods. Similarly, Wang and Zhao [4] explored CNN-based noise reduction approaches, highlighting their ability to preserve critical medical details.

Further, Howard et al. [5] proposed adaptive histogram equalization for enhancing X-ray images, significantly improving image contrast and diagnostic visibility. Liu et al. [6] developed a deep learning framework for lung disease classification using enhanced CXR images, reinforcing the importance of image preprocessing. Alshaye et al. [7] introduced hybrid filtering techniques that combine multiple denoising strategies for optimal results. Additionally, Gupta and Singh [8] conducted a comparative analysis of histogram equalization techniques, concluding that adaptive methods outperform traditional approaches in medical imaging applications. These studies collectively underline the necessity of noise reduction and enhancement techniques in medical image processing, serving as the foundation for this research.

III. REMOVING NOISE FROM CHEST X-RAY IMAGES

There are two types of noises in Chest X-ray images, which effect the accuracy of classification.
a. Salt and Pepper Noise
b. Gaussian Noise
a. Salt and Pepper Noise
Salt-and-pepper noise is a type of noise commonly found in digital images, characterized by randomly occurring white (salt) and black (pepper) pixels. It is typically caused by transmission errors, dust, or sensor faults in imaging devices. This noise appears as sharp intensity transitions, making images look grainy and distorted.
Algorithm: Remove_Salt_Pepper_Noise
Input: Noisy Image
Output: Denoised Image
Procedure
1. Read the input image.
2. Define a filter window size (e.g., 3×3).
3. For each pixel (excluding borders):
a. Extract the neighboring pixels within the filter window.
b. Sort the pixel values.
c. Replace the current pixel with the median value from the sorted list.
4. Store the filtered image.
5. Return the denoised image.
b. Guassian Noise
Gaussian noise is a statistical noise that follows a normal distribution (bell curve) and is often introduced in images due to sensor noise, low light conditions, or electronic circuit interference. It appears as random variations in pixel intensity, making images look blurry or grainy.
Algorithm: Remove_Gaussian_Noise
Input: Noisy Image
Output: Denoised Image
1. Read the input image.
2. Define a Gaussian kernel (e.g., 3×3) with standard deviation σ.
3. For each pixel in the image:
a. Extract the neighboring pixels within the kernel window.
b. Compute the weighted sum using the Gaussian kernel.
c. Replace the pixel with the computed value.
4. Store the filtered image.
5. Return the denoised image.

IV. HISTOGRAM EQUALIZATION

Histogram Equalization is a technique used to improve the contrast of an image by redistributing the intensity values. Below is a step-by-step explanation with a 3-bit image (intensity levels 0 to 7) and 20 pixels**:**
Step 1: Define the Pixel Intensity Distribution
Consider the following grayscale intensity values in the image and their corresponding pixel counts Total number of pixels = 20.

Intensity (0-7)	Pixel Count
0	2
1	3
2	3
3	4
4	2
5	2
6	3
7	1

Table 1: Intensity and Pixel count
Step 2: Compute the Probability Density Function (PDF)
The PDF is found by dividing each pixel count by the total number of pixels:
Count PixelsPDF(i)=Total PixelsPixel Count(i)

Intensity	Pixel Count	PDF
0	2	2/20 = 0.10
1	3	3/20 = 0.15
2	3	3/20 = 0.15
3	4	4/20 = 0.20
4	2	2/20 = 0.10
5	2	2/20 = 0.10
6	3	3/20 = 0.15
7	1	1/20 = 0.05

Table 2: PDF calculation
Step 3: Compute the Cumulative Distribution Function (CDF)
The CDF is calculated as:
CDF(i)=CDF(i−1)+PDF(i)

Intensity	PDF	CDF
0	0.10	0.10
1	0.15	0.25
2	0.15	0.40
3	0.20	0.60
4	0.10	0.70
5	0.10	0.80
6	0.15	0.95
7	0.05	1.00

Table 3: CDF calculation

Step 4: Compute the Equalized Intensity Values

The new intensity values are obtained using:

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

Intensity	CDF	New Intensity
0	0.10	1
1	0.25	2
2	0.40	3
3	0.60	4
4	0.70	5
5	0.80	6
6	0.95	7
7	1.00	7

Table 4: New intensity values

Step 5: Replace the Old Intensities

Now, replace each old intensity in the image with the 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

The image now has a better contrast with more evenly distributed intensity values.

V. EXPERIMENTAL RESULTS

Two datasets namely X1 and X2 are collected. X1 is collected from public domain. All the images are Chest X-ray images. There are two lables one is normal and other is abnormal. Second data set X2 is original dataset collected from labs. Two types of noises salt and pepper as well as Gaussian noise were removed from the dataset and then Histogram Equalization is applied. Both datasets have equally number of chest X-ray images. ResNet50 is trained seperately on both datasets. Accuracy is recorded. The following table shows the details of accuracy.

X1 – Dataset	X2 - Dataset
88.34	92.45

Table 6: Accuracies of two datasets

VI. CONCLUSION

This study demonstrated the effectiveness of noise removal and histogram equalization in improving the quality of chest X-ray images for medical diagnostics. By comparing a public domain dataset with a manually enhanced dataset, we observed a significant improvement in classification accuracy using ResNet-50. The accuracy for the public dataset was 88.34%, whereas our enhanced dataset achieved a higher accuracy of 92.45%. These results validate the importance of preprocessing techniques in improving deep learning model performance. Future work can explore advanced noise reduction methods and their impact on different deep learning architectures for enhanced medical image classification.

REFERENCES

[1] K. Suzuki, "A review of deep learning in medical imaging: Image segmentation and disease detection," Artificial Intelligence in Medicine, 2020.

[2] S. M. Anwar, M. Majid, A. Qayyum, M. Awais, M. Alnowami, and S. M. Khan, "Medical image analysis using convolutional neural networks: A review," Journal of Medical Systems, 2018.

[3] H. J. Kang, J. H. Lee, and Y. H. Cho, "Noise reduction methods for medical X-ray images using deep learning techniques," IEEE Transactions on Medical Imaging, 2021.

[4] R. Wang and Y. Zhao, "Denoising of medical images using wavelet transform and CNN-based models," IEEE Access, 2020.

[5] P. G. Howard, B. S. Deveraj, and M. I. Patel, "Enhancement of chest X-ray images using adaptive histogram equalization," IEEE Transactions on Biomedical Engineering, 2019.

[6] T. Y. Liu, H. C. Hsu, and K. M. Lin, "A novel

deep learning framework for lung disease classification using enhanced chest X-ray images," IEEE Journal of Biomedical and Health Informatics, 2021.

[7] M. R. Alshaye, A. H. Raza, and C. J. Simmons, "Noise reduction in X-ray images using hybrid filtering techniques," IEEE Transactions on Image Processing, 2021.

[8] N. Gupta and P. Singh, "Comparative analysis of histogram equalization techniques in medical imaging applications," IEEE Signal Processing Letters, 2021