ENHANCED PNEUMONIA DETECTION USING IMAGE PROCESSING TECHNIQUES AND DEEP LEARNING

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ABSTRACT

The following report focuses on using image processing techniques to improve pneumonia's prediction rate using chest X-ray images. A neural network is trained to first evaluate without using any techniques to set a baseline. Different preprocessing techniques are then applied, and the neural network is trained again. Results are compared to find the best technique that would improve pneumonia prediction by using the same chest X-ray images.

***Index Terms*—** digital image processing, pneumonia, medical image analysis, chest X-rays, deep learning

1. INTRODUCTION

Computer-Aided Disease Diagnoses (CADD) is a continuous innovation process and new ideas to ease human life. The ultimate goal of CADD is to detect diseases from medical images in digital form. Many bio-medical imaging technologies are available in modern days, such as Radiography (X-ray image), CT-Scan, ECG, Ultra-sound, MRI, etc. All these medical imaging are best suited depending on the type of diseases detected from the human body. The X-ray is a readily available and low-cost imaging technology solution to capture an image of lungs affected by Pneumonia.[1] The following Figs.1(a) and 1(b) depict X-ray images of lungs, which are Normal and have Pneumonia, respectively.

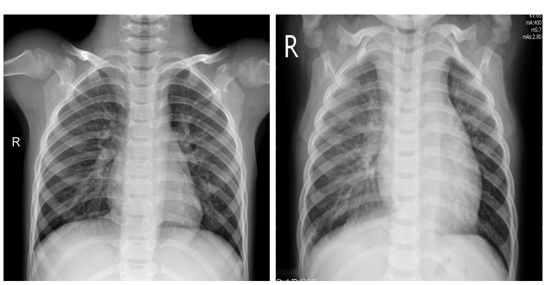

Fig. 1. (a) Normal Lungs (b) Pneumonia Lungs

To design a comprehensive CADD system for human X-ray images, one needs to understand image processing's basic methodology. This paper has proposed using image processing techniques to enhance the X-ray images and improve Pneumonia's detection in the lungs. For our comparison of our models, we have used accuracy as our comparison factor. Our paper's structure is as follows: Section 2 talks about the dataset which we used, our deep learning model, and the preprocessing techniques used for training. Section 3 describes the methodology for every technique used and describes what effects it brings on the images. Section 4 finally discusses all the results accumulated from the above methodology and shows us our paper's final result.

2. METHODOLOGY

This section has discussed the methodology and the flowchart of the proposed method for image preprocessing. We have divided it into three sub-sections Dataset, Flowchart for Training and Flowchart of Preprocessing. The dataset subsection tells us the the These flowcharts tell us how we would proceed in the code and how the images are enhanced.

2.1. Dataset

The dataset used in this project consists of two types of X-ray images. The first category of images consists of an ordinary person without Pneumonia and has regular lungs. The second category of images consists of a person diagnosed with Pneumonia and has affected the lungs. The dataset has been of been taken from the paper by Kermany et al. [2]

2.2. Flowchart of Training

Deep learning technology applied to medical imaging may become the most disruptive technology radiology has seen since digital imaging. We have used a convolutional neural network (CNN) for training chest X-ray images, which hierarchically stacks multiple layers of neurons, forming a hierarchical feature representation.
To compare our medical image analysis's benefit, we apply the same model first on unprocessed images and then on preprocessed images. The summary of our CNN model is shown in Fig 2.

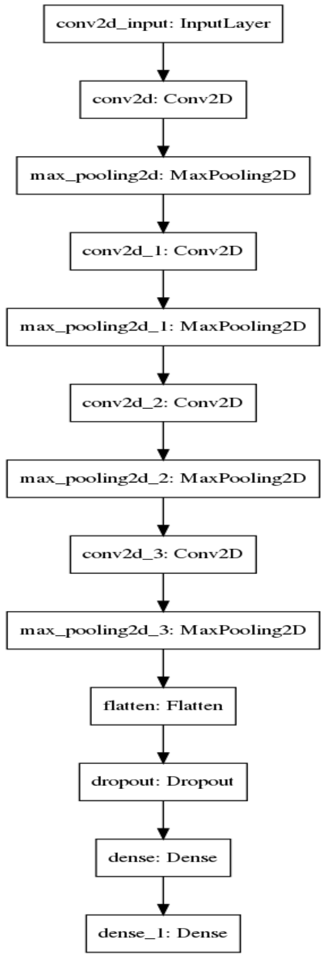

Fig. 2. Summary of our Convolutional Neural Network

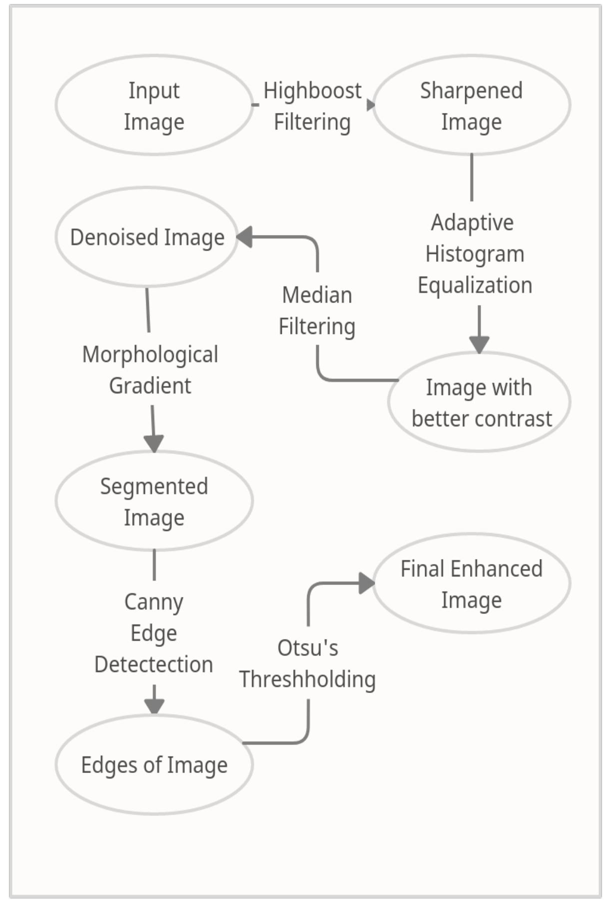

Fig. 3. Image Analysis Preprocessing

2.3. Flowchart of Preprocessing

Modern day medical imaging extracts data using techniques like X-ray, CT and MRI scans. However, we are still short of tools with which to convert all this data into useful information. In the discussion that follows, we highlight state-of-the-art applications of medical image analysis [3].
We have used a combination of various image processing techniques to extract more data from our dataset containing chest X-ray images. The summary of our image preprocessing techniques is shown in Fig 3.

3. MODEL

This section about the model describes each image processing technique in detail. Each of the image processing technique is defined and their benefit to the enhancement of the image is discussed. At the end we also see the progression of the image processing techniques through the photos and a sample photo is shown.

3.1. Highboost Filtering

Highboost filtering is used to emphasize high frequency components representing the image details without eliminating low frequency components. The following formula is used for highboost filtering:

$$g_{mask} = f(x, y) - f'(x, y)$$

$$f_{highboost} = f(x, y) + k \cdot g_{mask},$$

where $f'(x, y)$ is the blurred image and $k = 2$.
This results in a sharpened image by amplifying the edges (as shown in Fig 4).

3.2. Adaptive Histogram Equalization

Histogram equalization is used to improve contrast in images. Adaptive histogram equalization improves on this by transforming each pixel with a transformation function derived from a neighbourhood region. This significantly improved the contrast in our X-ray images as shown in Fig 4.

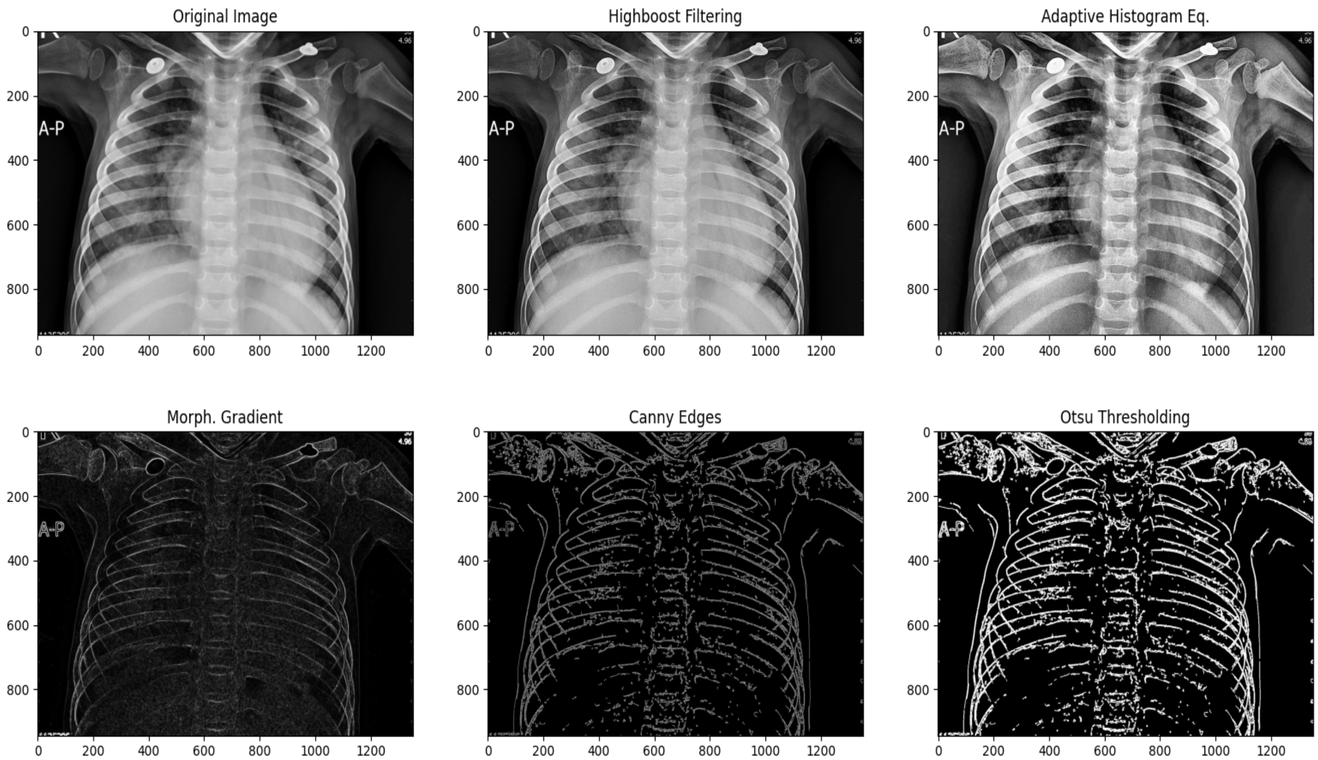

Fig. 4. Images after each Preprocessing step

3.3. Median Filtering

Median filtering is a non-linear noise removal technique which helps remove noise from an image. A median filter runs through the image pixel by pixel, replacing each pixel with the median of neighboring entries. This is very helpful in removing salt and pepper noise from images.

3.4. Morphological Gradient

Morphological gradient is the difference of the dilation and the erosion of the image. It gives us an image which has each pixel value which indicates the contrast intensity of every close neighborhood of that particular pixel. We used this process to perform segmentation on the X-ray images which makes them easier to analyze (as shown in Fig 4).

3.5. Canny Edge Detection

The Canny edge detector is used to detect edges in images using a multi-step algorithm. It is one of the most popular methods of edge detection. We have used edge detection to extract structural information about the X-rays. This also helps in highlighting internal organs and inconsistencies in the lungs, making it easier for our neural network to identify features. The same has been shown in Fig 4.

3.6. Otsu's Thresholding

Otsu's method is an adaptive thresholding technique for binarization in images. It runs through all possible threshold values, and can find the optimal threshold value of input image [4]. We have used Otsu's threshholding to further highlight the edges in our Canny edge detected images. We can see this apparent edge-amplification in Fig 4.

4. RESULTS

We carry out our investigation in two steps. First, we will train and test our model on our original dataset without any preprocessing (50 epochs) and find out our baseline accuracy. This baseline accuracy helps us to set a standard for our future preprocessing techniques and to help us tell whether each of these techniques is beneficial or not.

After training our model on the initial dataset, we run our validation data to find the accuracy, the accuracy and the loss in training and validation has been shown in Fig 5 and Fig 6 respectively.

The baseline accuracy that we set is 71.43% on the validation dataset. This accuracy will act as a benchmark for other preprocessing techniques. We can see that the loss is also more significant in training our model with the original

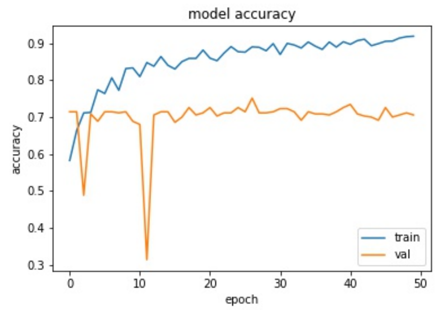

Fig. 5. Training and Validation Accuracy on Original Dataset

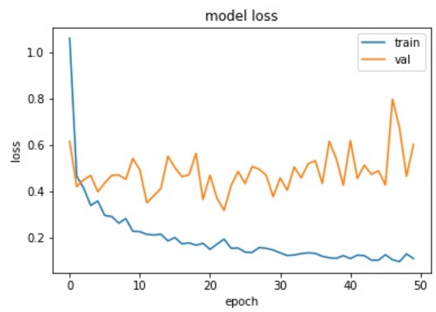

Fig. 6. Training and Validation Loss on Original Dataset

images.

Now we apply our proposed image processing techniques to the images in our dataset. After all the processes are applied, we again train our model but now on the enhanced images (50 epochs), and then check for the accuracy again. The accuracy and loss of training and validation on the enhanced image dataset has been shown in Fig 7 and Fig 8 respectively.

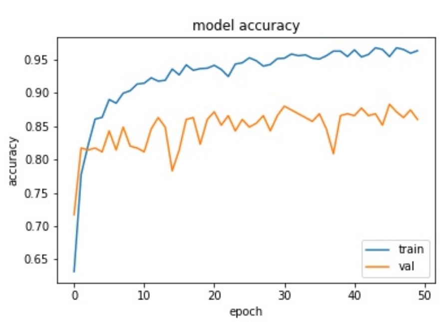

Fig. 7. Training and Validation Accuracy on Enhanced Image Dataset

The accuracy of the enhanced image dataset is 88.29% on the validation dataset. Thus we can see that there has been a significant improvement in the accuracy when we apply the image processing techniques to the dataset.

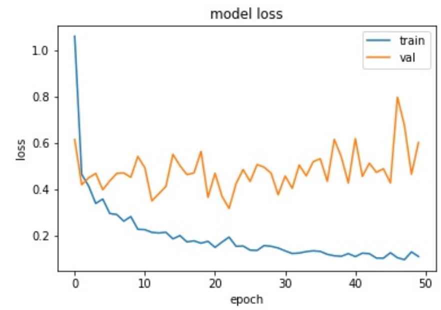

Fig. 8. Training and Validation Loss on Enhanced Image Dataset

There is almost a 17% increase in the accuracy, which shows that the improvement is enormous, and the pneumonic lungs' prediction has improved significantly. Hence, we can summarize our output accuracies and loss in Fig 9 and Fig 10 respectively.

Without Processing	With Processing
71.43%	88.29%

Fig. 9. Comparision of Accuracy

Without Processing	With Processing
0.61	0.38

Fig. 10. Comparision of Loss

5. CONCLUSION

In conclusion we can see that the proposed method for X-ray image enhancement provides significant improvement in the accuracy of Pneumonia prediction. This result could also help in enhancement of other images of similar sort and can help in the further advancement in CADD as discussed in the introduction.

6. REFERENCES

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