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Enhancing Medical Images using Non-Local MEANS Filter to Detect Abnormalities in the Chest Region

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Abstract – Reading a medical image accurately requires special training and lots of experience. Even radiologists who have trained in this field for several years tend to make mistakes. These mistakes have on many occasions have cost the lives of many people. A study states that about 40% to 54% of the malpractice claims are due to the misinterpretation of radiologic images. The advances in artificial intelligence have paved the way for making the computer learn any kind of pattern just like the human brain and use the acquired knowledge to predict the unknown factors. The main challenge in reading medical images is the noise that is caused while capturing, and storing them. Removal of the noise during the pre-processing step of an image is very essential before feeding it into a neural network. The main intent of the project is to remove noise from the radiologic images using the Non-Local Means (NLM) Algorithm and to build a simple Convolutional Neural Network(CNN) model to detect abnormalities in the radiologic images. In the already existing models, very complex algorithms are used with several layers of neural networks that would result in an increase in time and memory. This paper also focuses on using the same CNN model to detect the abnormalities, in this case, Pneumonia and Breast cancer in both X-rays and Ultrasound images. A result of very high accuracy of 95.11% was obtained while detecting the abnormalities from the medical images.

***Keywords* – Non-Local Means Algorithm, Convolutional Neural Network, noise, Pneumonia.**

I. INTRODUCTION

The reading and interpretation of medical images have to be done with extreme caution as this would cost the life of an individual if not done right. The reading of the medical images is majorly done by radiologists who have been trained for several years. Although such extreme precaution is taken in order to read these radiologic images, radiologists at many a time commit mistakes in interpreting the abnormalities right. In a study [2] looking at fifty-eight pairs of MR images, observed by two radiologists showed that 47% of the cases were misinterpreted due to observer bias. The leading cause of mortality and disease severity is mainly attributed to the errors in diagnosis. The third leading cause of death in the United States is the miss in diagnosis or misinterpretation of the radiologic images[1].

The human error that leads to several lawsuits can be reduced by the application of artificial intelligence(AI). Several advances in the medical field such as disease diagnosis, robot-assisted surgery, etc., have led to excessive reliance on AI. The application of AI helps in reducing human errors, labor, and time.

Previously several studies have been carried out in detecting pneumonia from X-rays. In these studies, the pre-processing of the image like denoising had not been performed. Additionally, in some studies 500 iterations had been done to achieve the accuracy of about 92.9%[12]. One iteration would take about 10 hours and it involves multiple iterations to get an accuracy of about 95% by training with only around 200 images[14].

In this research, a deep learning model using the convolutional neural network architecture that reads the input as images are trained with a labeled set of training data. A testing set is then used to test the accuracy of the trained model in detecting the abnormalities in these images.

This paper also intends to remove the noise from the medical images that are caused during capture, storage, or transfer of the images. The noise removal is performed by using the Non-local Means (NLM) filter. NLM is the best filter for medical images because the same pixel is distributed across the entire image and NLM distributes the average of the pixels in the dominant space throughout the entire image. This filter also helps in preserving the texture of the images which would otherwise be blurred in other types of filters. Preserving the textures is very important for the medical images as the tiniest details make huge differences in diagnosis.

This paper discusses the model containing several layers viz., an input layer for receiving the medical images, a pre-processing layer that uses the NLM filter to remove noise, several hidden layers where the neurons extract the features from each image and learn about them, and an

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output or the fully connected layer. In addition to all these layers, activation functions are used in between the layers for the transfer of the features among the layers.

II. METHODOLOGY

1. Dataset

The chest X-ray images of pneumonia and Ultrasound images of breast cancer are obtained from the Kaggle site. There are a total of 5856 images in each of the categories. They are further subdivided into three sets viz., 'Train', 'Test', 'Validation'. The 'Train' set is used to train the model. The 'Test' set is used in evaluating the trained model. The 'Validation' set is used to evaluate the accuracy of the model. All the images in both the datasets are labeled as 'Pneumonia' and 'Normal' in the chest X-ray images and 'Cancer' and 'Normal' in the Ultrasound images.

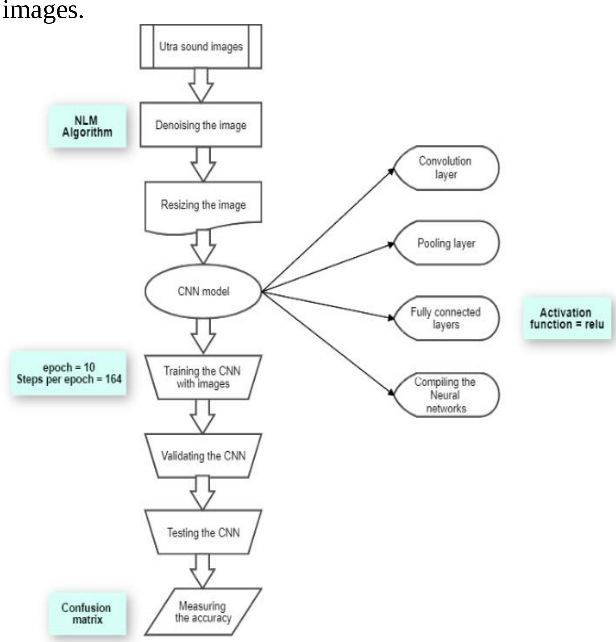

Fig.1. Workflow.

2. NLM Filter

The nonlocal means filter (NLM) was first proposed in a study [3], and it had been known for its efficient removal of additive white Gaussian noise(AWGN). It is a very simple filter. While removing the noise, the filter also preserves the edges. With all these properties, NLM has a very important part in image processing.
The filter is represented as[4],
(1)

where Ga is a Gaussian kernel, h is a filtering parameter and C(x) = dz is a normalizing constant.
The image obtained from the NLM algorithm has a greater PSNR value than the noisy image. After denoising an image, the image should be resized, so that CNN would read the image and more features could be extracted from the image. Resizing the image depends on the factors like size of GPU and total epochs.

3. CNN Model

The resized images are read by the default functions of the Keras library. The images are then read using the data generators, instead of the traditional 'for' loop mechanism as the 'for' loop would increase the time and memory consumption. The data generators are used to read the images for both training and testing operations. A data generator is capable of loading the required amount of data straight from the source folder, converting them into training data and training targets.
For training the model, the batch size is mandatory to process the images. The data generator processes the images in terms of batch size that are provided. The batch size is generally modified according to computational resources and model performances. The batch size used here is '32'.

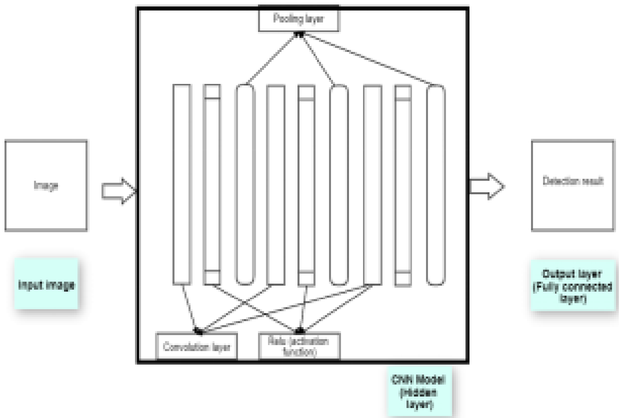

Fig. 2. The CNN model architecture.

The next step is to build the model. The model is built with five blocks, consisting of two convolution layers, a pooling layer with Max pooling, and batch normalization. The activation function 'relu' is used and 'sigmoid' that is used for binary classification problems is used before the two fully connected layers. The CNN model is compiled with Adam optimization function that optimizes the model and learns the correct classification of the image.

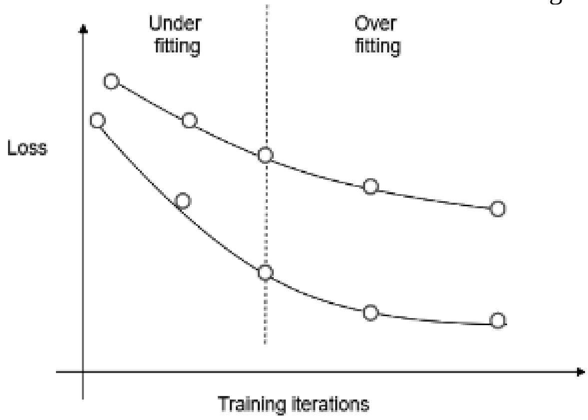

Fig.3. Under-fitting and Over-fitting,

When the CNN model is fed with the training set and it begins to learn all the features, the problem of underfitting

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or overfitting occurs. This would affect the accuracy and the precision of the model which would make it unreliable. Thus this problem of underfitting or overfitting is overcome by incorporating two methods: Model checkpoint and early stopping.

III. RESULTS

After running the model which takes around three hours for the entire dataset to be trained and tested, the accuracy and loss are studied. The model shows no underfitting or overfitting. In order to fully ensure that the model shows no underfitting or overfitting, the method of early stopping is used. This makes sure that when the model is trained up to the baseline level, the training is stopped.

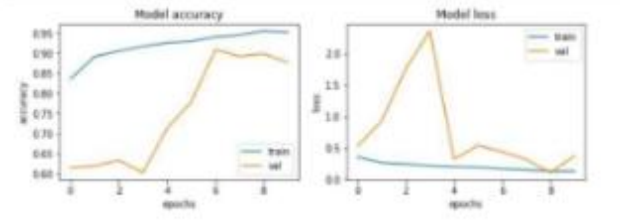

Fig.4. Model Accuracy and Loss for Chest x-ray images.

After feeding the test set and validation set into the model, the training accuracy of 95.11% was obtained. The testing accuracy of 93.75% was obtained. A confusion matrix is used to get a summary of the model. The results of the confusion matrix showed that precision is 84.19%, recall is 99.74%, and the F1 score is 91.31.

Similarly accuracy for the ultrasound images of breast cancer that is obtained from the same model is 80%.

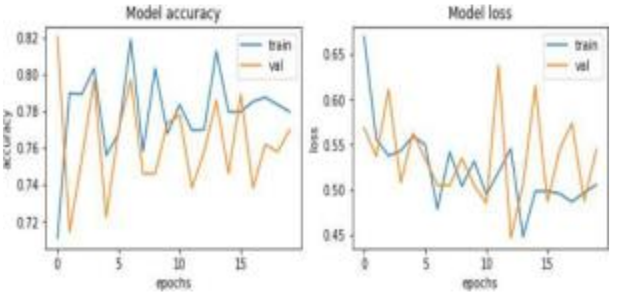

Fig.5. Model Accuracy and Loss for Ultrasound images.

The same model is used for both the types of radiologic images i.e. Ultrasound and X-ray. The accuracy of the model is the highest and utilized only three hours to train resulting in less time and computation power.

IV. CONCLUSION

A simple CNN model which is fed with a denoised image has resulted in high accuracy with less time and iterations. The major challenge in medical image processing, i.e. the noise is handled by using the NLM (Non-local means) filter. Another challenge of underfitting/Overfitting is eliminated by using Model Checkpoint and early stopping. Further, the accuracy of the Ultrasound images is to be improved by using a larger dataset. This simple model would be of major help in diagnosing Pneumonia and Breast Cancer at a considerably faster pace and more accuracy. Hence the medical errors could be minimized.

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