Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606

Volume 05 Issue 01
2023

Research Article
https://doi.org/10.56979/501/2023

N-Dimensional X-Ray Image for Lungs Abnormalities Detection Using Deep Learning Technique

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Received: April 03, 2023 **Accepted:** June 03, 2023 **Published:** June 05, 2023.

Abstract: This paper presents a methodology to generate an N-dimensional, stacked image dataset. The chest X-Ray images dataset, acquired from the NIH database is used to develop an N-dimensional images dataset. The NIH published a list of chest X-ray images to aid the scientific community in the research work. The dataset consists of a large number of X-ray images of multiple chest diseases. In this work, we selected 3,500 images, distributed equally to the five chest findings. The dataset generation process involves suppressing undesired distortions and enhancing desired features on the radiological images. The feature enhancement is achieved by applying multiple filters on the classical digital X-ray images. The multi-filtering technique aims to enhance and elaborate abnormalities in the image, letting the classification models detect and extract slight variations in the image features. The presented work aims to get an improved classification result on chest diseases to help decision-making easy and less erroneous. The preprocessed dataset is then fed to the deep convolutional neural network (CNN) models like VGG16, ResNet, and Inception. The models are custom-tailored to accept N-dimensional stacked images and transfer learning is also applied to the models thus eliminating the need for retraining the models. A lightweight deep CNN model is also designed to feature considerably fewer layers and weights. The model is quickly trained on underpowered devices. The two model sets are then evaluated to detect and classify the chest disease in the formulated images. The evaluations are applied to chest X-ray images of multiple classes. The experimental results that the models applied to the proposed multichannel image dataset showed 95% higher classification accuracy than the experiment results from the original X-ray image dataset.

Keywords: N-Dimensional Images; CNN; Machine Learning; Deep Learning; Transfer Learning; Classification.

1. Introduction

Medical science is a very vast field. In the medical field radiologist detect details from X-Rays images to detect and diagnose some issues in the human body including abnormalities in the chest or defects in the skeleton parts such as bones and teeth Skull etc. Some of the major chest abnormalities are effusion, Pneumonia, nodule, atelectasis, cardiomegaly, edema, and many others [1]. The radiologist can identify the infected region in the X-ray image. However, classifying the abnormality in the chest X-ray images can sometimes be a difficult task for the medical expert. It is because medical experts, doctors, and radiologists, manually classify chest X-rays based on some visual examination. Sometimes vulnerabilities in the X-ray images are not quite visible due to their grayscale pixels. On the other hand, there exist automatic intelligent systems that identify normal and abnormal images and subsequently classify them based on features present in the image. For example, computer-aided diagnosis (CAD) systems are designed to aid medical experts in the detection of diseases from X-ray images. The CAD systems, however, have not provided good results regarding the classification of images at the required accuracy [2]. The role of CAD systems was limited to detecting disease regions in the X-ray images that help doctors in making decisions.

In recent years, the world moved towards, machine learning algorithms and deep learning systems applied to medical science. Some of the deep convolutional neural networks are reported to provide superhuman results to aid the classification of different phenomena in the given images. The success of getting more accurate results motivated the research community to apply those machine learning algorithms and deep neural networks to medical images for disease classification. All done due to its power of getting and extracting features from different angles in the radiograms. However, the traditional approaches it is required a large amount of data and huge computing power for training the deep CNN-based disease detection models [3].

The objective of this study is to develop a new algorithm for the solution of a problem and its focus is the development of an image preprocessing approach that aids existing classifiers to get higher classification accuracy for multiple chest diseases. Our focus is to apply multiple feature-enhancing techniques to the given digital X-ray images to highlight features from multiple perspectives. For this purpose, the chest X-Ray images dataset acquired from the National Institutes of Health (NIH) database is used. The dataset contains a list of chest X-ray images and was published to the scientific community by the NIH Clinical Center [4]. The given X-ray image is first denoised by applying mean and median filters. The filters will remove Gaussian noise and impulse noise in the image, respectively. The pseudo-color transform method is then applied to the noise-reduced grayscale X-ray images using indexed coloring. In this technique, the image is colonized based on its grayscale value which is mapped to the full RGB color range. The pseudo-coloring reveals the image's hidden texture which would not be visible under a grayscale tone. The resultant images are then treated by augmentation techniques to produce an N-dimensional stacked images dataset. The defined dataset is then fed to existing deep CNN-based classification models. The transfer learning is applied to the models to adapt the structure of the stacked images in their input feed. The models are then evaluated for the lung diseases classification performance on the original X-ray images dataset and the defined, N-dimensional dataset. The experimental results show that the models applied to the proposed dataset showed higher classification accuracy as compared to the results from the original X-ray image dataset [5].

The organization of the work in this article is defined as follows. The existing neural network-based techniques for image classification are discussed in section 2. The proposed image preprocessing methodology is discussed in section 3 and in section 4 model configurations in described with its experimental analysis being discussed in section 5. Finally, section 6 concludes the work.

2. Background Survey

Many scientific papers have been published to enhance the identification of pneumonia or other diseases using artificial intelligence, expert systems, and neural networks. Recently, medical centers and hospitals have started to incorporate artificial intelligence systems and technologies in some disciplines to increase disease detection accuracy. Many approaches and models have been implemented that have led to improved diagnostic performance. A coevolutionary neural network, 121_layer trained on Chest X-ray14 is the most important of which the ChexNet algorithm is designed that can detect certain forms of inflammation. The Chex Net algorithm, from chest X-rays, performs at an exceeding radiologist practicing stage [6]. An advanced deep-neural network method has been developed and used by Joseph R. Ledsam and Julia H. Miao the used deep learning-based prediction and classification models to predict coronary heart disease in patients and improve diagnostic accuracy, at New York University medical school [7]. Their research included two components of existing diagnoses and models of classification.

This approach has been tested in the Alzheimer's Disease Neuroimaging Initiative (ADNI) database, where MRI images are the input and output modalities. Results showed that prior approaches were substantially outperformed by the method [9]. Ikhsan, Ili Hussain, Aini Zulk fley, MohdTahir, Noorita Mustapha, and Aouache wrote a paper on the analysis of x-ray image enhancement methods for vertebral bone segmentation [4].

During the process of image segmentation, image enhancement is a vital step and procedure, particularly for X-ray images. This step increases the accuracy and performance of the segmentation, Amplification of the difference and sharpness of the picture will expand the precision of the resulting modules for an independent infection-finding framework [10]. In this research, an examination of different strategies for preprocessing procedures for vertebral bone division is introduced. Three strategies are viewed which are histogram leveling, gamma remedy, and difference-restricted versatile histogram adjuster. This work expects to look at and evaluate the accuracy and precision of the procedures that are utilized to enhance picture quality [11].

On the classification side, various models based on deep learning technologies have been presented [15, 6, 17, 18]. Such models can learn from complex data that, unlike any other image recognition and categorization technology, can process huge volumes of data to ensure high processing speed and precise results. An important preprocessing activity in abnormalities classification in chest radiographs is presented by Ho and Gwak in [8]. The study in [9] applies multiple filters to extract features from the given chest radiographs to get an integrated feature vector which improves the classification performance of the classification models for certain chest diseases. The filters, however, are applied to the raw X-ray images. The grayscale images can mislead the models to generate false negative or false positive alarms [12]. Preprocessing images to elaborate features is highly desired to further improve abnormality detection in chest radiographs [13-14].

3. Proposed Methodology

In this section, we proposed an image classification model as shown in Figure 1. The proposed model consists of two sections; image preprocessing and image classification. The image-preprocessing stage is to get a multichannel (stacked) X-ray image dataset from given grayscale X-ray images. The first step in the image preprocessing stage is to apply multiple image descriptors to the grayscale X-ray images. Each image descriptor is fed with an image to get features enhanced. The output image from each descriptor is then put to the next descriptor sequentially. The last step in the preprocessing stage is an augmentation to get a multichannel(stack) image dataset. In the final stage, the multichannel image dataset is input to the deep convolutional neural network (DCNN) model for training the model. A detailed description of each component of the dataset generation and model training is given in the following sections.

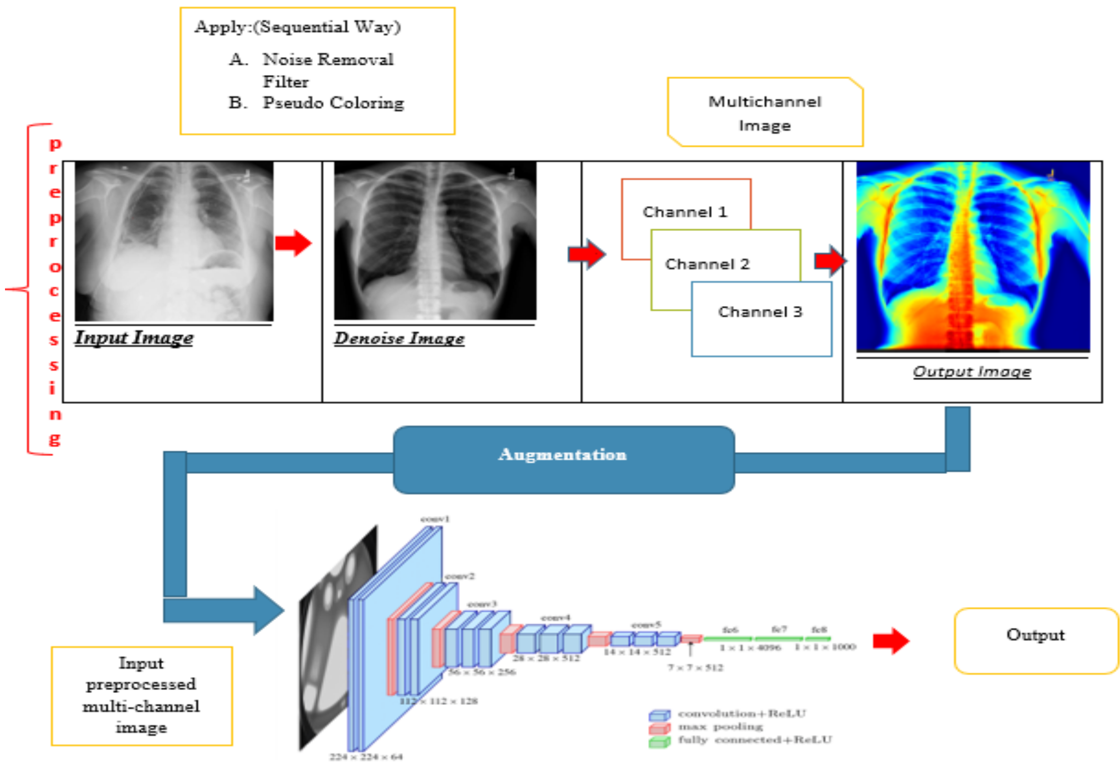

Figure 1. Proposed Image Classification Model

3.1 System Components

The chest X-Ray images dataset, acquired from the NIH database is used to develop an N-dimensional images dataset [16]. The NIH published a list of chest X-ray images to aid the scientific community in the research work. The dataset consists of a large number of X-ray images of multiple chest diseases [19,21,23]. In this work, we selected 3,500 images, distributed equally to the five chest findings. The Salt and Pepper noise creates random dark and bright regions in the image. The bright spots are the main disease markers in the X-ray images [18,20,22]. For example, the main identification of Atelectasis or Edema is the bright lung region as shown in Figure 2.

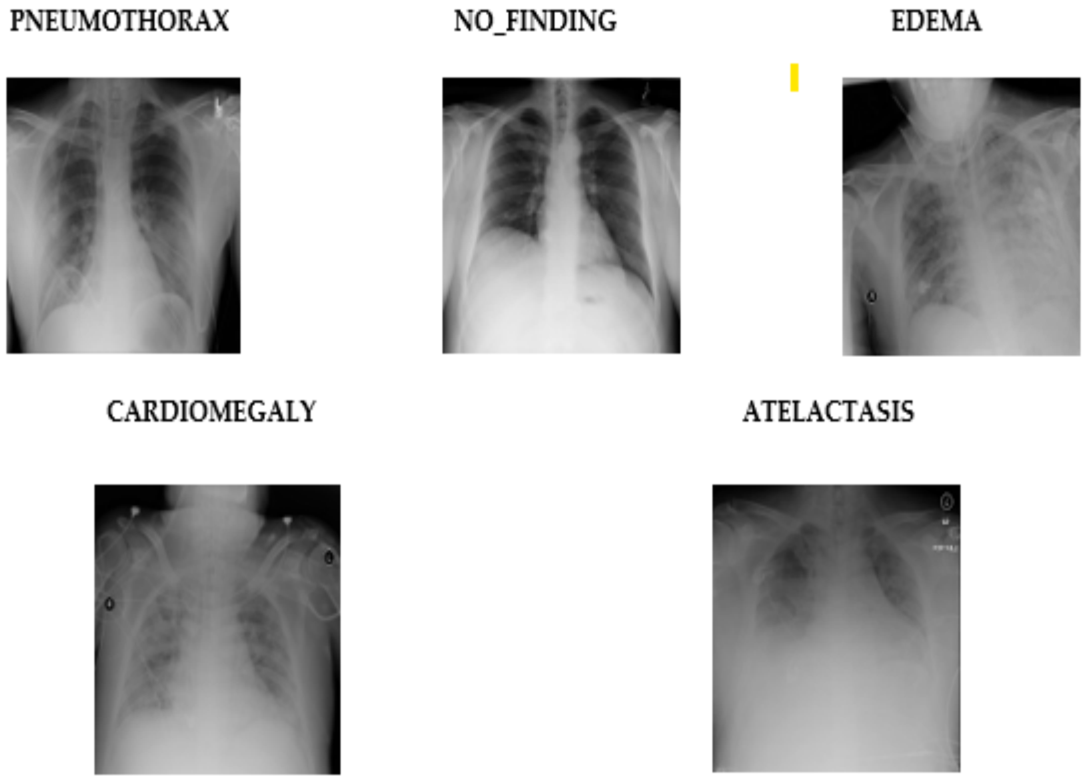

Figure 2. Chest disease sampled radiographs

3.1.1 Image Preprocessing

The classification models, to work on the images were trained on the ImageNet dataset. According to the ImageNet requirement, the image size is 224x224 scale. However, X-ray images in the NIH dataset are of different sizes. Therefore, the images are resized according to the norm to get an accurate size to input to the ImageNet pre-trained classification models.

3.1.2 Denoising and Pseudo-coloring Images

Certain problems such as noise build-up and signal distortion can occur during image processing and that can make certain issues in the process of denoising [24-27]. Therefore, it is one of the key steps to work on it for the consistency of the dataset. There exist multiple noise types like the photon, thermal, Poisson, speckle, Gaussian, Salt and Pepper, etc., that can distort image quality. However, compared to the rest of the noise types, the two forms of noise, Gaussian and Salt and Pepper create a highly distorting phenomenon to the features in the X-ray images. The false patches in the image cause wrongly identified diseases. Image processing makes it simpler to curtain the noise to the input data. We have applied the Mean and Median filters to the images for de-noising. Next, the pseudo-coloring technique is applied for experimental analysis as shown in Figure 3.

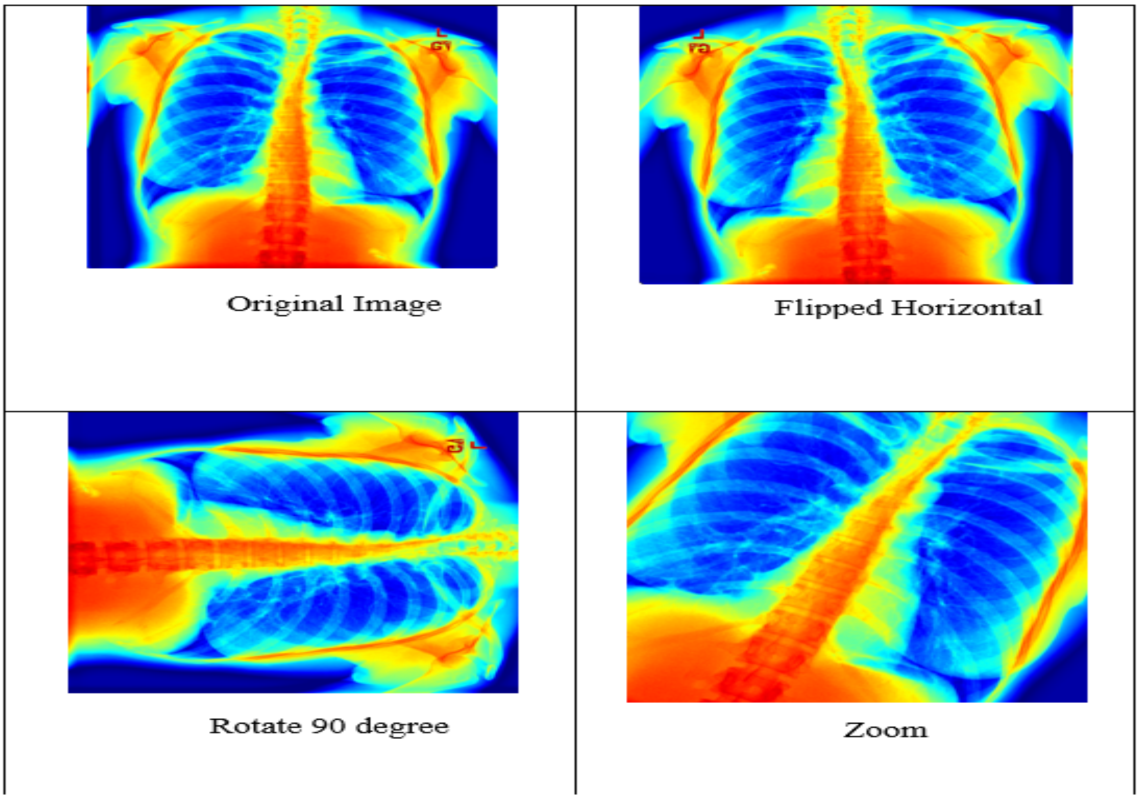

Figure 3. Image Transformations

4. Model Configuration

The deep neural network models VGG16, ResNet50, and InceptionV3 are discussed in this section. In our models, a SoftMax classifier, 1024,512, and 256 neurons are distributed among five fully connected layers [28]. The deep neural networks have 1,182,211 trainable parameters for VGG16 and 2,755,075 for ResNet50 and InceptionV3, respectively. Additionally, during training, the bias and weight parameters of our neural network-based classifiers are learned by backpropagating the error in order to reduce the categorical cross-entropy using the Adam optimizer. Following the training procedure, the models were evaluated using several sets of hyper-parameters (only appended layers as pre-trained networks remain frozen) [29]. A vector of probability that an input image belongs to one of the classes is the output of the SoftMax classifier [30]. The greatest value's related class is the last one, and its position is then transferred back to a corresponding class. Through the Python API Keras, the code for the transfer-learning models is accessible to the general public [31]. On GoogleColab's GPU-equipped servers, our algorithms were trained.

5. Results and Discussions

Setting pre-trained network parameters to non-trainable causes this relatively brief interval, and as a result, the gradient brought on by misclassification only passes through the added layers. As can be seen in Figure 4, the real-size photographs with hundreds of thousands or millions of pixels were originally shrunk to a fixed format, which was advantageous for the duration. The maximum platform usage period, which is up to twelve hours, was the main issue with training. We were able to identify a relatively decent epoch after which models were overfitting training data by looking at the error calculated on a validation set. After stopping the training procedure, the final results were calculated as the average of every result attained up until that point.

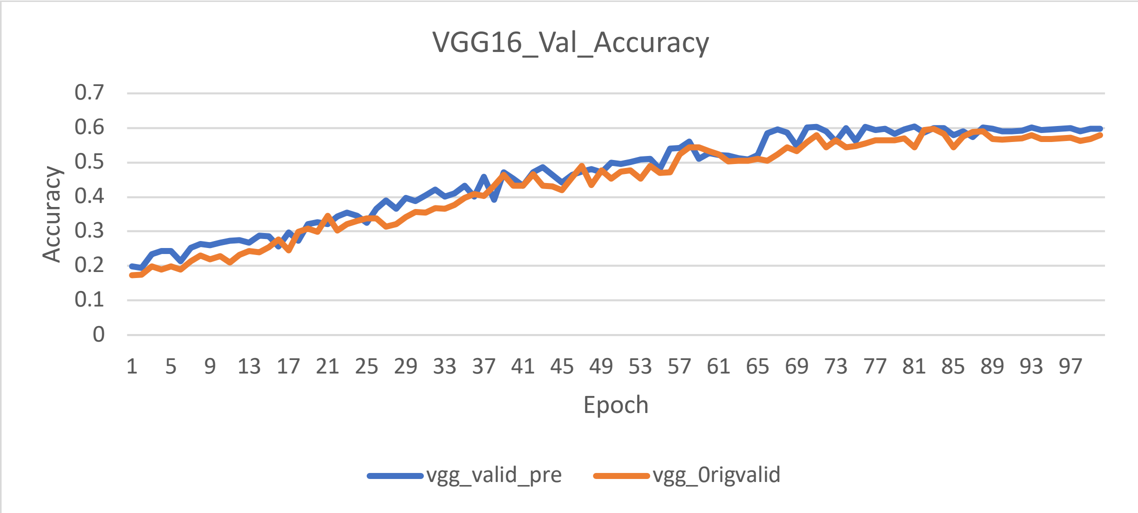

Figure 4. VGG16_Val_Accuracy_Comparison

The next stage was to display how well-chosen models performed on the omitted data, as seen in Figure 5. It describes the ResNet_Orignal and Preprocessed data comparison through a graph.

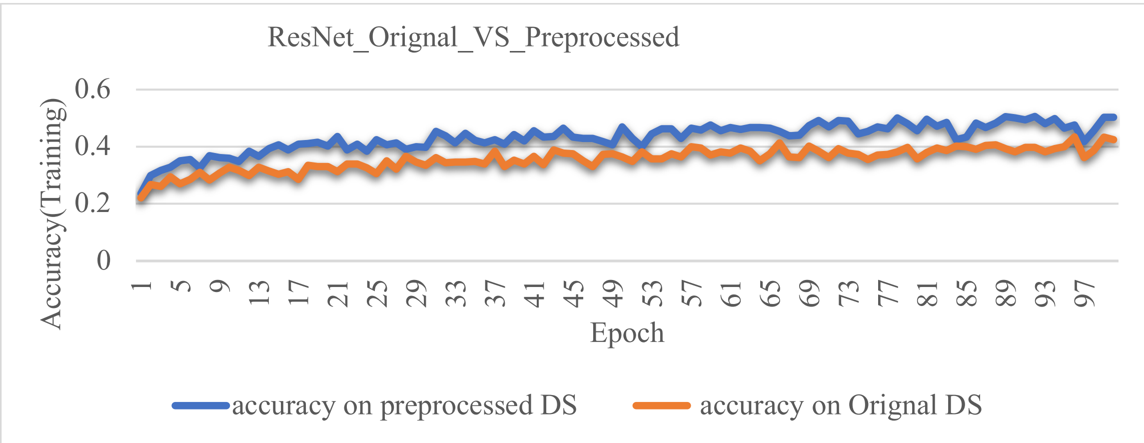

Figure 5. ResNet_Accuracy_Comparison

5.1 Validation Accuracy

In the validation accuracy test, the model is tested on unknown images. So, in the graph Epochs display on the x-axis, and Validation accuracy has taken on the y-axis. The below graph describes the validation accuracy of the ResNet model on the original dataset. The result of ResNet accuracy original is shown in Figure 6.

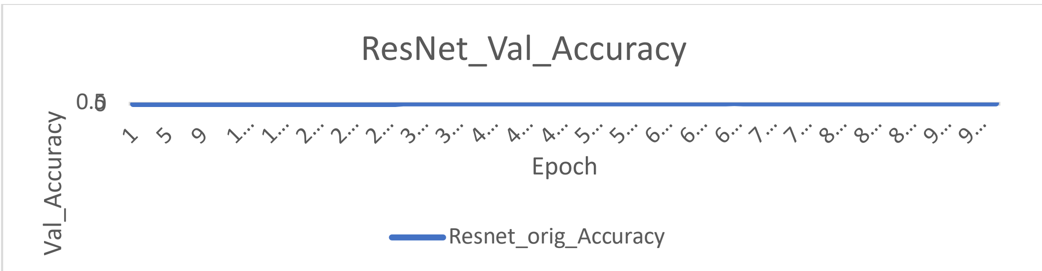

Figure 6. ResNet_Accuracy_Validation_orignal

The comparison of ResNet original accuracy and pre-accuracy is shown in below Figure 7.

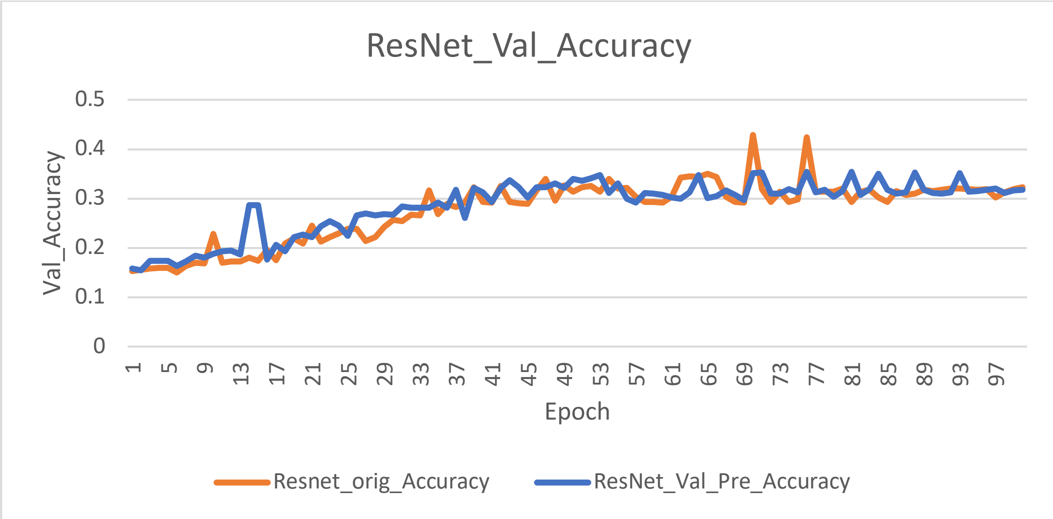

Figure 7. ResNet_Val_Accuracy_Comparison

5.2 Comparison of Original Dataset

In this section, we check how our under-consideration models behave on the original dataset, and which one gave more accuracy among these models. A comparison of all models on the original or unprocessed dataset is shown in the form of the graph below which gives a pictorial description in Figure 8.

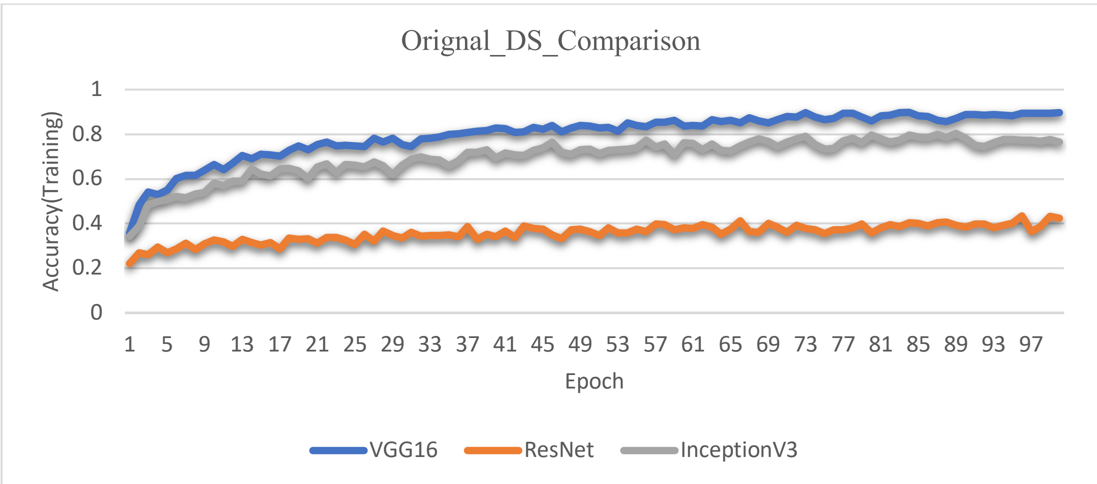

Figure 8. Comparison of Accuracy

Here we concluded that VGG16 gave more accuracy among all, after VGG16 InceptionV3 gave more accuracy, and ResNet gave less accuracy as compared to others.

5.3 Comparison of Preprocessed Dataset

In this section, we check how our under-consideration models behave on the preprocessed dataset, and which one gave more accuracy among these models. A comparison of all models on the preprocessed dataset is shown in the form of the graph below which gives a pictorial description reflected in Figure 9.

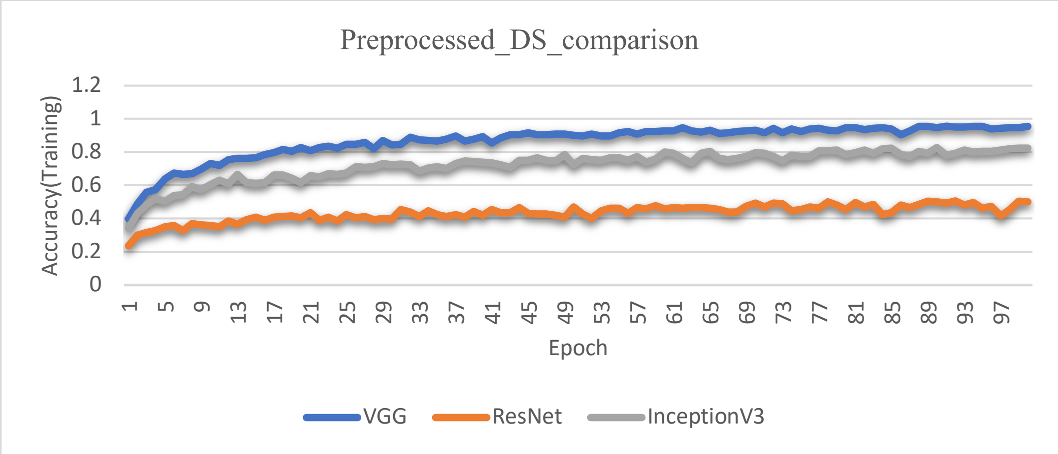

Figure 9. Comparison of Preprocessed Data Set

Here we concluded that VGG16 gave more accuracy among all, after VGG16 InceptionV3 gave more accuracy, ResNet gave less accuracy as compared to others on the preprocessed dataset.

5.4 Result Evaluation

Here we compare all results that we get from all models on both datasets (original and Preprocessed), and we evaluate whether accuracy improved or not on the methodology that we adopt in our framework. so, our methodology performs well and accuracy improved as shown in the graph reflected in Figure 10.

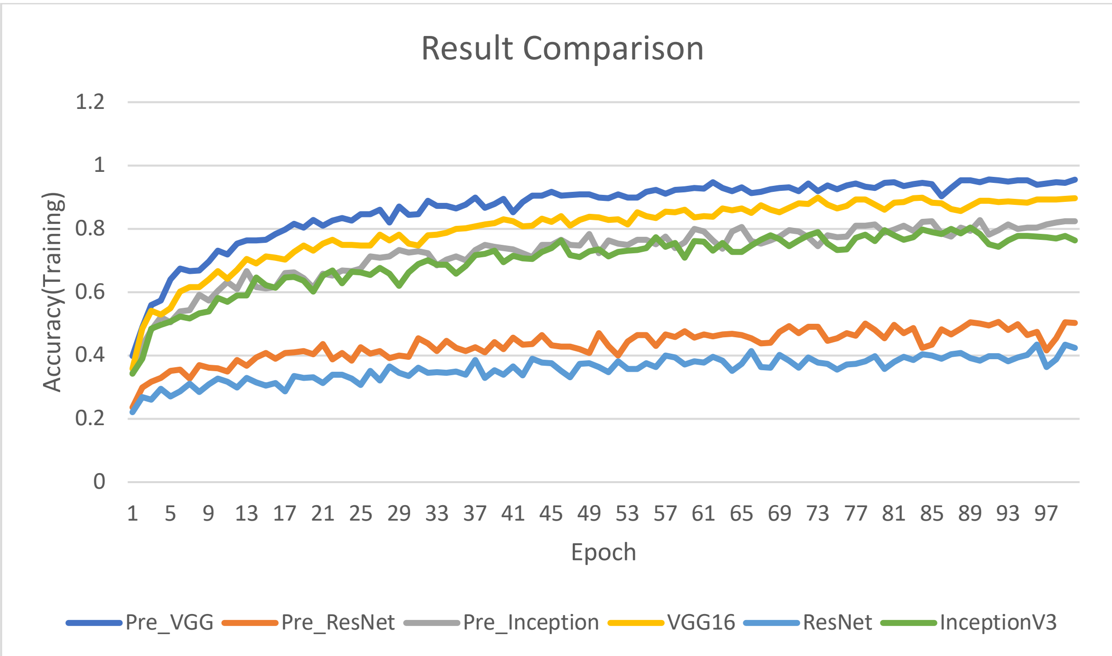

Figure 10. Results Comparison

This Graph tells which model gave more accuracy on datasets under the same parameters, preprocessed VGG16 gave more accuracy (95%). InceptionV3 gave (82%) training accuracy on preprocessed datasets. Resnet gave less accuracy as compared to the above two as shown in Figure 11.

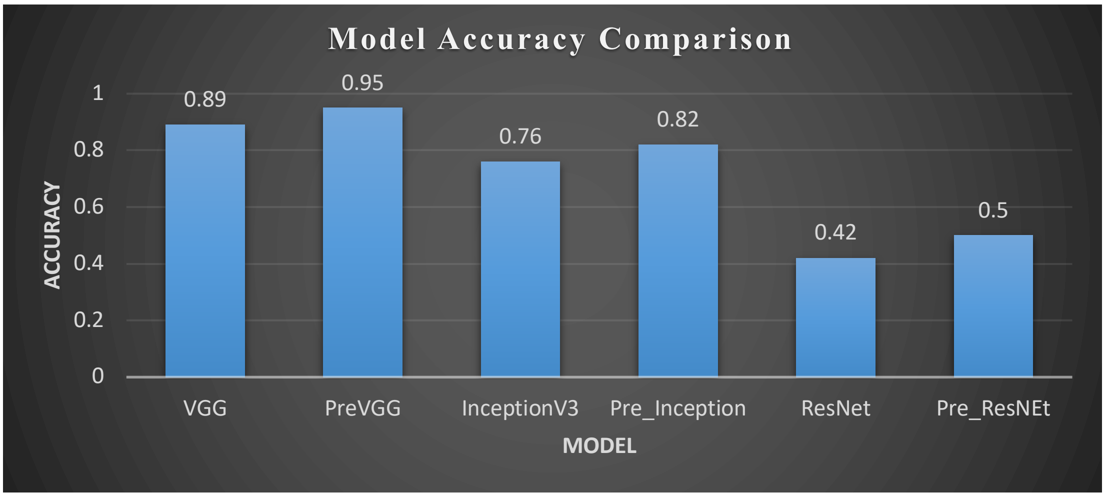

Figure 11. Results Comparison with accuracy

6. Conclusion and Future Work

In this paper, we have proposed a methodology for improving the classification accuracy of existing neural network models. For the said purpose we have defined a novel preprocessing technique applied to the input image set. In this technique, we have applied multiple descriptors to the images to get the required image. In this technique, the original dataset in which we first denoise the image then applies pseudo coloring on the output image, converts it to a multichannel stack image, and finally apply augmentation for overcoming overfitting.

This multichannel image is then the input of DCNN models. The ImageNet pre-trained models such as VGG16, ResNet, and InceptionV3 are used, and transfer learning is applied to implement disease classification tasks. Evaluation of models trained on an original and preprocessed dataset of Chest X-Ray images is done to compare performance in terms of classification accuracy. The experiment is restricted to classifying the disease diagnosis in chest x-ray into five types, Edema, Cardiomegaly, Pneumothorax, Atelectasis, and no finding. The experiment result shows that all models achieve higher classification accuracy and promising classification results on the proposed preprocessed image dataset as compared to the original image dataset. Surprisingly, the CNN models such as VGG16 and InceptionV3 networks have higher accuracies compared to ResNet. It is probably due to parameters that are set during the training of these models. As we changed parameter accuracy also varies. A team working at Google Inc. recently published a paper for a newly designed CNN (convolutional neural network) model called Efficient-Net. The model sets new records for both accuracy and computational efficiency. In the future, we can use Efficient-Net to classify chest diseases using our preprocessed dataset to get better accuracy results.

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