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Multiple Lung Diseases Classification from Chest X- Ray Images using Deep Learning approach

FethyaSeid Yimer[1], Abel Worku Tessema[1,2], Gizeaddis Lamesgin Simegn
[1]Biomedical Imaging chair, School of Biomedical Engineering, Jimma Institute of Technology, Jimma University, Jimma, Ethiopia, fethya.seid19@gmail.com
[2]Ulsan National Institute of Science and Technology (UNIST), Ulsan, Republic of Korea, abelworku1221@gmail.com
[1]Biomedical Imaging chair, School of Biomedical Engineering, Jimma Institute of Technology, Jimma University, Jimma, Ethiopia, 1time.et@gmail.com

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ABSTRACT

Lung diseases are disorders in the lung that affects proper functioning of the breathing system. Chronic Obstructive Pulmonary Disease, lung Cancer, pneumonia, tuberculosis, and pneumothorax are prevalent in most developing countries. Diagnosis of lung diseases is usually performed through visual inspection of chest X-ray images, especially in low resource settings. This procedure is time consuming, tedious, and subjected to inter- and intra-observer variability leading to misdiagnosis. The purpose of this research was to develop a method for automatic classification of multiple lung disease from chest X-ray images using Xception deep learning method. The data required for training, validation and testing the system was collected from Jimma University Medical Center Radiology Department and National Institute of Health (NIH) chest X-ray dataset repository. All the images have been pre-processed prior to training. An accuracy, sensitivity, and specificity of 97.3%, 97.2%, and 99.4%, respectively have been achieved for multi-class classification. The developed system can be used as a decision support system for physicians, especially those in low resource settings where both the expertise and the means is in scarce. The system also allows capturing of images from radiographic films extending its implementation in areas where only the conventional X-ray machines are available.

Key words: - Lung disease, Multi-class Classification, Image processing, Chest X-ray, Deep Learning, Xception

1. BACKGROUND

Lung diseases are disorders of the respiratory system that affects the lungs causing breathing problems. Lung cancer, Chronic Obstructive Pulmonary Disease(COPD), lower respiratory infections (pneumonia), and tuberculosis (TB) are leading causes of respiratory morbidity and mortality among adults [1]. COPD is the fourth leading cause of death worldwide caused by tobacco smoking[2], environmental and occupational factors[3].

Diagnosis of lung disease include pulmonary function test using spirometer machine for COPD, blood and sputum analysis for pneumonia and TB, CT scan for lung cancer, and chest X-ray imaging for all. For lung diseases diagnosis, clinicians usually integrate their medical knowledge with chest X-ray image to obtain the nature and pathological characteristics of lung diseases and decide on treatment options[4].

Evaluating chest X-ray images requires adequate time and systematic examination. All parts of the image need to be examined in an orderly manner to detect all possible abnormal findings on the image. Lungs are examined by step-by-step assessment of the chest X-ray images looking for cavitation, consolidation, infiltration, blunted costophrenic angle, and small broadly distributed nodules.Starting at the apex or base, and then each region (upper, mid, and lower) of the lung is compared from side to side. Moreover, hidden areas such as apical areas underlying the clavicles, perihilar and paratracheal regions, retrocardiac and infra-diaphragmatic areas require careful examination.

Visual inspection of chest X-ray images is prone to error, and is a great challenge since it requires high level of expert knowledge. The task is very time consuming, and leads to inter- or intra-observer variability.Introduction of computer aided diagnosis (CAD) systems in chest-radiography can help physicians to detect suspicious lesions that are easily missed, improving the accuracy of diagnosis. The concept of CAD for chest X-rays has made fast progress from using rule-based (RB) prediction to classical machine learning (ML) approaches upgraded to deep learning(DL) methods.

Several techniques have been proposed to diagnose and classify lung abnormalities based on rule-based systems[5-7]. Rule based systems require more memory and processing time as it demands deep knowledge of the domain as well as a lot of manual work. Generating rules for a complex system is challenging and tedious. Complex pattern identification is a challenging task in the RB approach. On the other hand, ML approaches enables to build a more powerful and intelligent decision-making systems by using the advantages of an artificial neural network. Several techniques using machine learning approaches have been proposed for chest X-ray image classification[8-12]. However, the algorithms in most studies have focused on the binary classification of lung disease. Most algorithms were developed for pneumonia[13-16]or pulmonary tuberculosis[17-19]detection even though there are various lung abnormalities in real-world clinical practice. This limits adoption of the proposed techniques for clinical diagnosis. Most of these works are also limited in accuracy making them unreliable. Hence, sensitive, accurate, and easy to use automatic system that can classify most prevalent lung diseases from chest X-ray images to help reduce the heavy workloads of radiologists and avoid misdiagnosis is required.

In this work, an accurate, reliable, and easy to use automatic system that classifies multiple lung diseases (Lung cancer, COPD, Pneumonia, TB, and Pneumothorax) has been proposed using the state-of-the-art deep learning approach.

2. MATERIALS AND METHODS

The general methodology of the system includes image data collection, pre-processing, data preparation, and classification. **Figure 1** demonstrates the general methodology employed in this study.

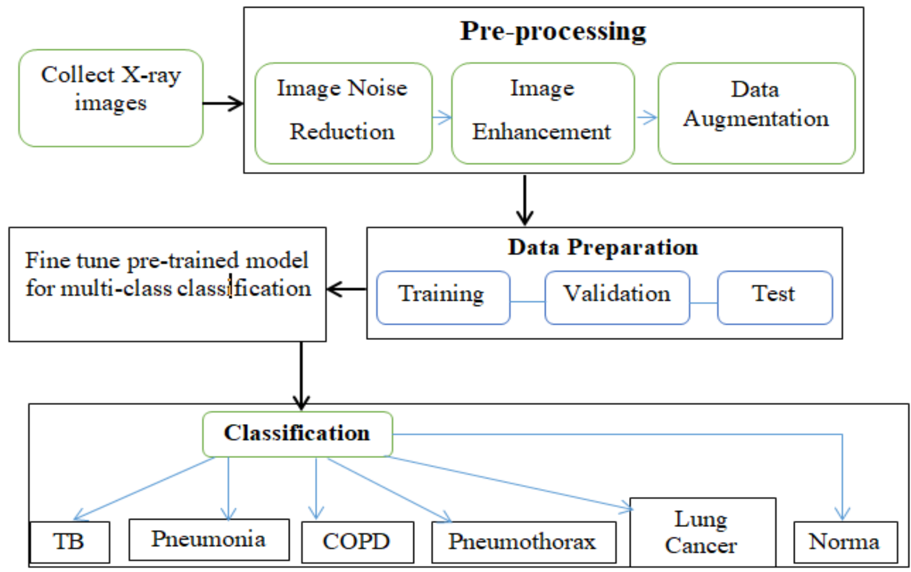

Figure 1: General block diagram of the proposed multiple lung disease classification system

2.1. Data Collection

Local chest X-ray images and online datasets were collected to train, validate, and test the model. A total of 11,716 label X-ray images were collected from National Institute of Health (NIH) dataset repository[20]. Additionally, 443 local chest X-ray images were collected from Jimma University Medical Center (JUMC) radiology department cross checked with the medical history of the patient for proper labeling with the diseases. An ethics approval letter (IRB 308/20) has been obtained from Jimma University's Institutional Review Board (IRB) for the use of the X-ray image data. Table 11 illustrates the type and number of image data collected from NIH and JUMC.

Table 1: Types and number of image data collected from NIH database and JUMC

Disease type	Data from NIH	Data from JUMC
Lung cancer	1823	12
COPD	717	9
Pneumonia	3875	153
TB	1680	110
Pneumothorax	2038	19
Normal	1583	140
Total	**11,716**	**443**

2.2. Pre-processing

The main purpose of pre-processing is to enhance the quality of images by removing artifacts and boosting important features. In X-ray radiography, usually images are in the form of gray scale and not every pixel will exactly detect the same photon to others, some pixels have more X-ray and appears darker, where as some pixels get fewer X-ray photons and appear brighter. However, this distribution of pixels is random and it has a shaded appearance which results a salt and pepper distribution. Generally, X-ray images are dominantly affected by salt and pepper noise(impulse noises), speckle and Poisson noises[21,22].

There are various de-noising techniques including Weiner filter, Gaussian filter, Median filter, and Mean filter. Median filter is the most effective filters used for removal of salt and pepper noises as well as speckle and Poisson noises on X-ray images[21-23].Median filter has been applied to all images in this study.

After the noise removal, image enhancement was performed using Contrast Limited Adaptive Histogram Equalization (CLAHE) technique[24,25]. Histogram equalization (HE), adaptive histogram equalization (AHE) and CLAHE were applied for comparison. CLAHE is the improved version of adaptive histogram equalization that operates on a small region on a gray scale image with limited contrast. CLAHE was developed to prevent the overall amplification of noise and affecting other wanted regions that adaptive histogram equalization can cause[24,26]. To apply CLAHE, first the image need to be partitioned intorectangular contextual regions.Then, the histogram equalization enhancement technique is applied on each and every tile of the image. Finally, bilinear interpolation is computed at the boundary pixels to avoid the visibility of boundaries between tiles.**Figure 2** illustrates the pre-processing procedure applied in this paper.

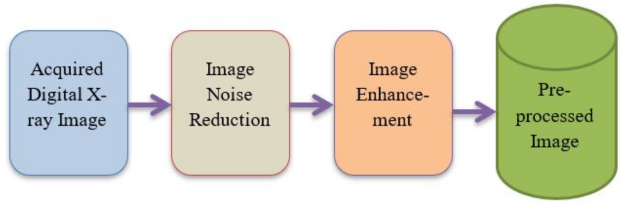

Figure 2: Image pre-processing steps including image noise reduction by median filter and enhancement using CLAHE

2.3. Image Augmentation

Limited data is a major challenge in deep learning models for image classification. Often, imbalanced classes can be related difficulty; while there may be sufficient data for some classes, equally important, but under sampled classes will suffer from poor class-specific accuracy. There are many ways to address complications associated with limited data and imbalanced classes. Image augmentation is one useful technique that can increase the size of the training set without acquiring new images[27,28]. In this paper data augmentation using rotation of 45, 180, 270 degrees has been applied to increase the number of data and resolve class imbalance. After image augmentation is applied on the pre-processed image, the total number of images increased from 12,159 to 17,751 images.In addition to this, the images were scaled to uniform size of 299 × 299 from the original 1066 × 1066 image size as required by the model.

2.4. Image Classification

In this work, multi class classification model has been used to classify X-ray images into six classes (normal, pneumonia, TB, COPD, pneumothorax, and lung cancer). Xception (Extreme Inception) model [29] was selected for classification in this work.Xception is a deep convolutional neural network architecture that is made up of modified depth wise separable convolution blocks and Maxpooling layers with residual connections. Xception reduces the high computational power and expensive operation of the standard convolution by using modified depth wise separable convolution. it is 71 layers deep and requires an image input size of 299×299.

Since the Xception model was pre-trained on non-medical image (ImageNet), fine tuning has been done in this research. The model was used as a feature extractor and classifier. Both its architecture and weight value (from ImageNet) were adapted. To achieve this, initial layers weights of the model which are generic were frozen during the training whereas the higher layers were fine-tuned. By using soft-max regression technique the probability distribution of each possible class was found and based on the most probable class the images were classified accordingly.

The activation function for each layer is Rectified Linear Unit (ReLu) because it does not activate all the neurons at the same time, dropout introduces regularization within the network to reduce over-fitting. As an optimizer, Adaptive Moment Estimation (ADAM) optimizer [30] was chosen for its best performance in terms of speed to converge and accuracy. Loss function for multi class classification was categorical cross-entropy, which is the standard loss function used to train neural networks to solve classification tasks[31].The following hyper-parameters have been selected during initial training: Batch = 32, Learning rate= 0.01, Epoch = 50. Then depending on the status of the training or convergence of the error, hyper-parameters (the batch and learning rate) were changed. As the number of steps increased, the learning rate was decreased and batch number was increased to make the loss more stable and converge to the smallest point possible. Loss values were calculated via forward propagation and learnable parameters were updated via back propagation by optimizers.

Before feeding the data to the network, dataset split was done for training and testing. Data were divided into train (80%) and test (20%) randomly. Among the 20%, 10% was used for validation, and the remaining 10% for test. A training set is used to train the network while a validation set is used to monitor the model performance during the training process, fine tune hyper-parameters, and perform model selection. The test set is used to evaluate the performance of the final model.

Table 2: Description of datasets used for training, validation, and testing Xception model.

	Normal	TB	Pneumonia	COPD	Pneumothorax	Lung cancer	Total
Training	2360	2360	2360	2360	2360	2360	14160
Validation	295	295	295	295	295	295	1770
Test	295	295	295	295	295	295	1770
Total	2950	2950	2950	2950	2950	2950	17700

2.5. Model Performance Analysis

A test set consisting of 295 images (10% of the total image data for one class) were given as input for the classifier to test the performance of the classifier. Using unseen dataset, the model performance was tested using a confusion matrix. The system saves the best result for the model during training, and after training is completed the model performance was analyzed with the saved weight. By using confusion matrix, the performance measure parameters including, accuracy, sensitivity and specificity were calculated.

3. RESULTS

3.1. Pre-processing

Figure 3 demonstrates the effect of median filter on the sample X-ray image along with their corresponding histogram plots. After applying median filter, salt and pepper noise observed in **Figure 3a** has been removed as shown in **Figure 3b**.

For image enhancement conventional HE, AHE and CLAHE were applied for comparison. **Figure 4** shows the effect of HE. The whole image contrast was affected, including the lesions. This effect can destroy the important features exhibited by the various abnormalities. **Figure 5** shows the effect of AHE. AHE improves the contrast of the image under question better than the standard HE. However, since background pixels share most of the count, theyover enhance the background noise. **Figure 6**shows the CLAHE enhanced image along with its histogram plot. CLAHE control the pixel value of the output image by clipping the highest histogram peaks and then equally redistribute the clipped pixels over the remaining gray-level ranges (**Figure 6d**).

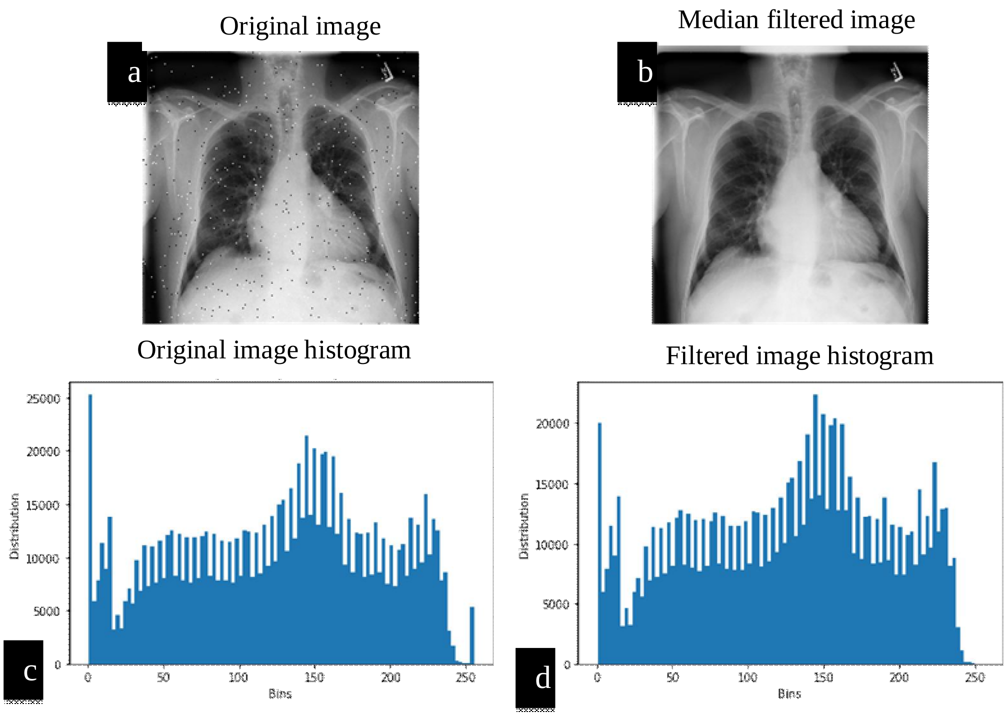

Figure 3: Result of de- noising. (a) Original image, (b) Filtered image (c) Histogram plot of the original image and (d) Histogram plot of the median filtered image

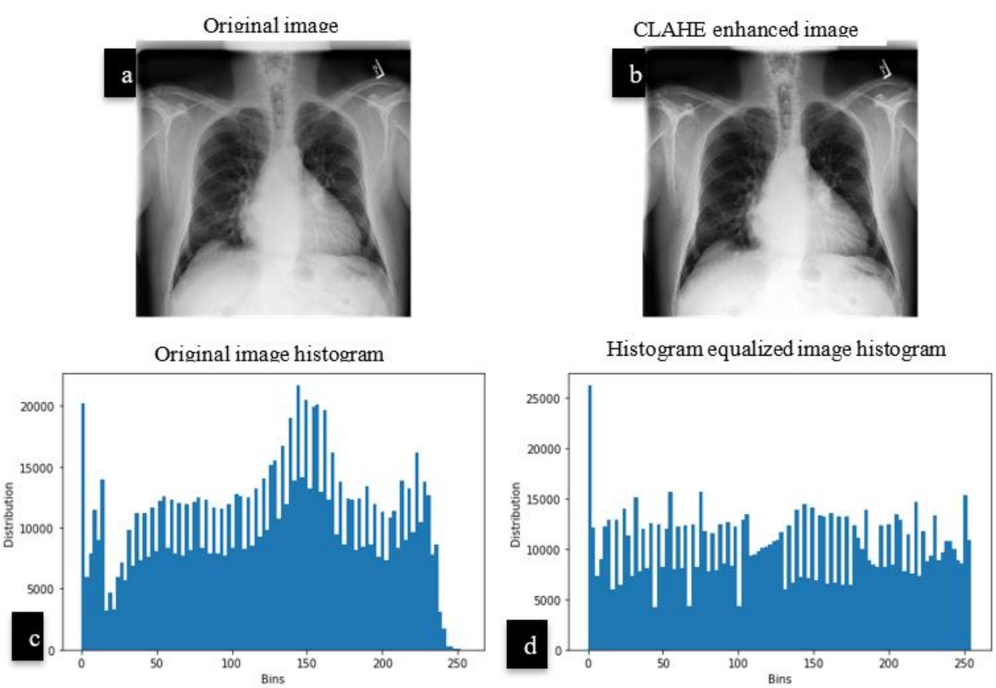

Figure 4: Effects of histogram equalization: (a) Original image, (b) Histogram equalized image, (c) Histogram plot for original image and (d) Histogram plot for Histogram equalized image

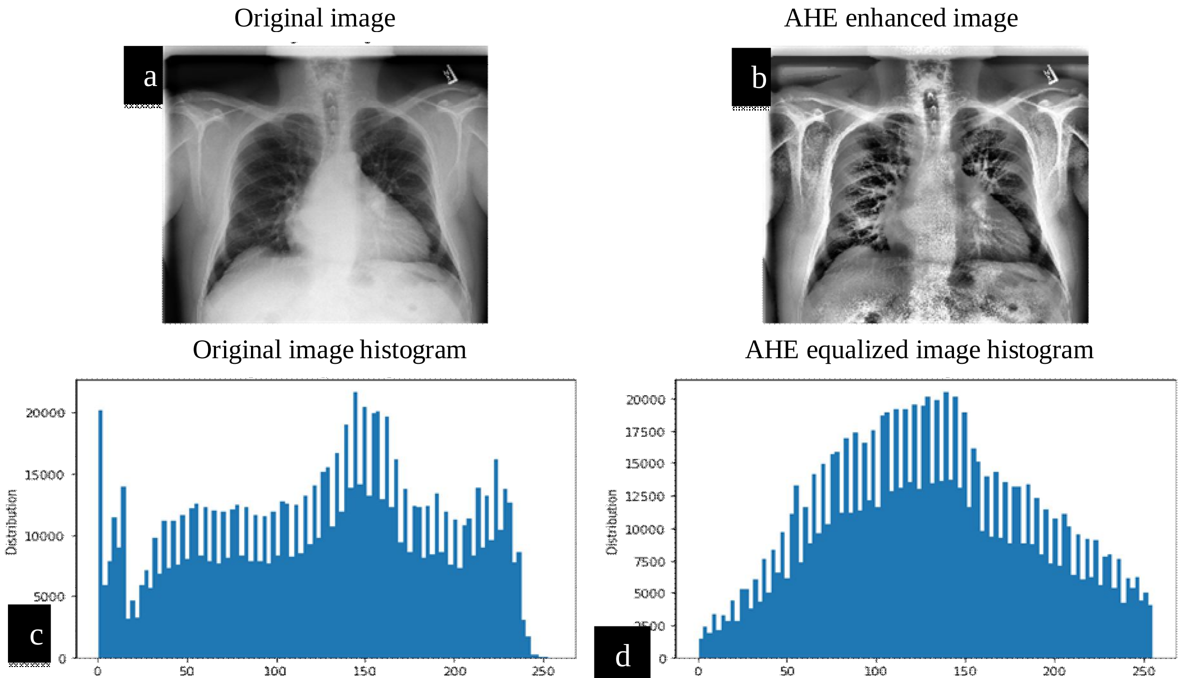

Figure 5: Effects AHE: (a) Original image, (b) Equalized image with AHE, (c) Histogram plot for original image and (d) Histogram plot for Equalized image.

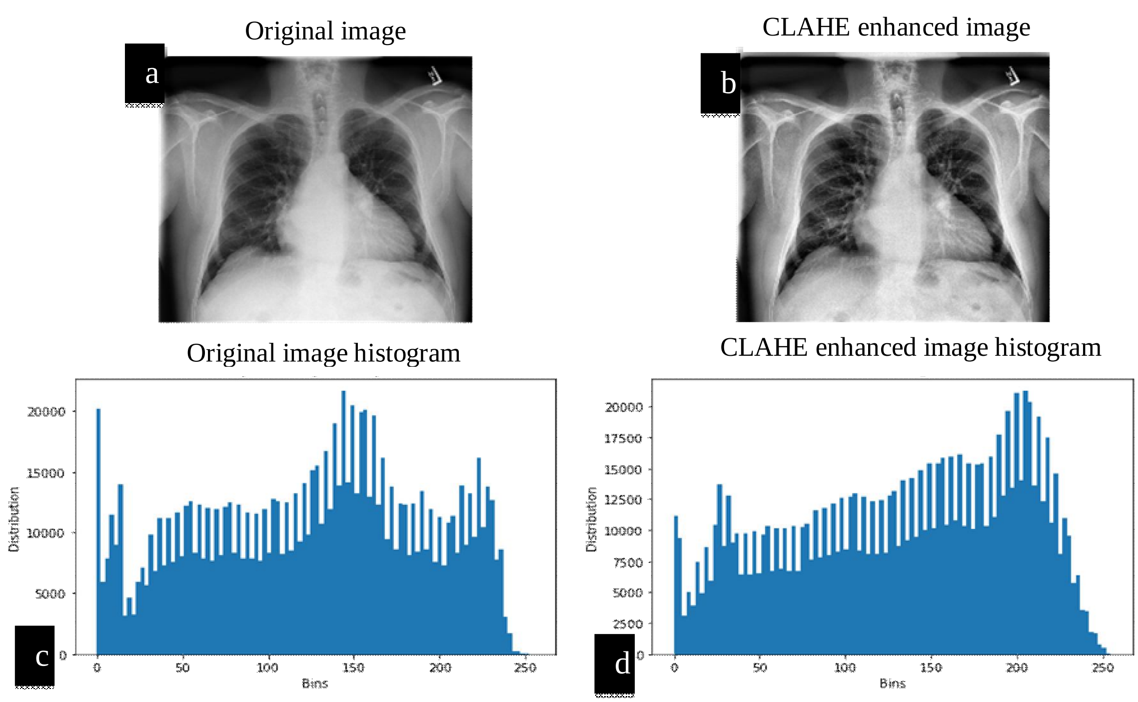

Figure6: Result of image enhancement using CLAHE (a) Original image, (b) Equalized image, (c) Histogram plot for original image and (d) Histogram plot for Equalized image

3.2. Classification

Figure 7 demonstrates the training and validation curves for the trained model. The curve shows the rate of improvement in learning and validating task with respect to time. The model converged and reached to 92% validation accuracy in just 10 epochs. The epoch size and learning rate of the model were 50 and 0.01, respectively.

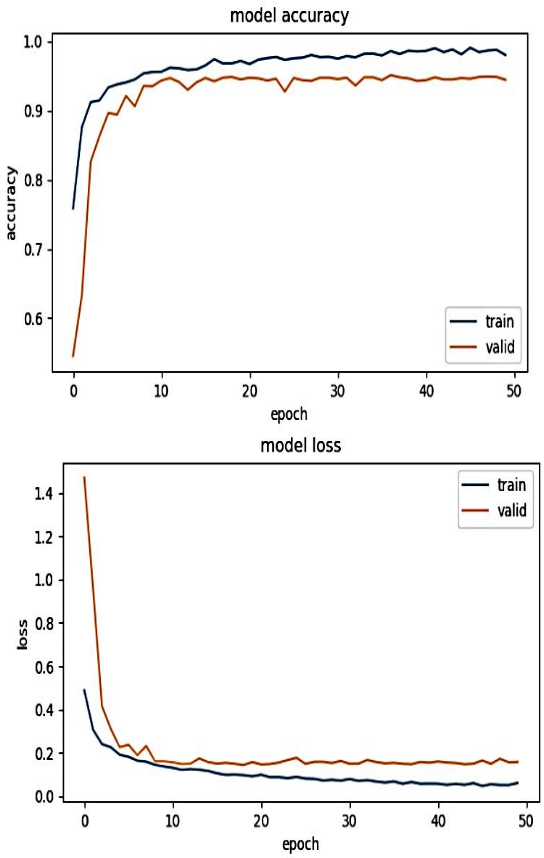

Figure 7: Training and validation curves the model.

3.3. Model Performance Analysis

The performance of the algorithm was evaluated classification accuracy, sensitivity, and specificity performance metrics. Confusion matrix (Table 3) was used to obtain the classifier performance metrics. The test set contains 295 images per class, which is 10% of the total data used. According to Table 3, 15 COPD images were misclassified (6 as pneumothorax and 9 as lung cancer). And from pneumothorax class 8 images are misclassified (5 as COPD and 3 as lung cancer). Similarly, from lung cancer class 22 images are misclassified (13 of as COPD and 9 as pneumothorax). All Normal images were classified correctly. Generally, an average 97.3% accuracy, 97.2% sensitivity and 99.4% specificity has been achieved using the model.

Table 3: Confusion matrix for X-ray images multi-class classification using the Xception model

	Normal	TB	Pneumonia	COPD	Pneumothorax	Lung Cancer	Sensitivity (%)
Normal	295	0	0	0	0	0	100
TB	0	295	0	0	0	0	100
Pneumonia	0	3	292	0	0	0	98.9
COPD	0	0	0	280	6	9	94.9
Pneumothorax	0	0	0	5	287	3	97.2
Lung Cancer	0	0	0	13	9	273	92.5
Specificity (%)	100	99.7	100	98.7	98.9	99.1	Accuracy = 97.3%

4. DISCUSSION

The common approach to diagnose lung disease is through visual inspection of the chest X-ray images. However, the current diagnosis method of lung diseases from chest X-ray images is tedious, time-consuming, and subjected to inter and intra-observer variability. Because of the complexity nature of chest X-ray radiography images and the limited number of radiologists, accurate and reliable classification of diseases remains challenging. Current classification of lung diseases using AI systems performs well with the state-of-the-art deep learning approach. However, most proposed techniques are either binary classifier or do not consider diseases prevalence. Limited reported accuracies are also a challenge for implementation or adoption of the systems in clinical setting.

In this research multi-class classification of top prevalent lung diseases have been developed based on Xception model. All the images have been pre-processed prior to feeding to the model. Median filter was used to remove noses from chest X-ray images, and CLAHE has been used to enhance the contrast of the images. A graphical user interface has been also developed for ease of use and implementation of our system.The performance of the algorithm was also evaluated using sensitivity, specificity, and accuracy performance metrics.

The result obtained from de-noising employed in this study showed that X-ray images that are affected by salt and pepper noses were properly filtered using Median filter (**Figure3**). The effects have been clearly seen on the histogram plot (**Figure3d**). The method also preserved the edges well in addition to removing noise.

Enhancing an image which has highly uneven histogram distribution using global histogram equalization may lead to unrealistic output image whose contrast is worse than the input image. It tends to change the mean brightness of the image to the middle level of the dynamic range and results in annoying artifacts and intensity saturation effects [32,33].This is shown in **Figure4**. Redistributing the highest peaks over the lowest histogram peaks using HE over-enhanced the lowest peak gray-levels or/and under enhances the highest peak gray-levels. On the other hand, AHE over□amplified the image including noises in relatively homogeneous regions of the image. The effects are visualized clearly on **Figure5**. CLAHE rectifies the limitation of AHE by removing the problem domain locally assuming the regions (tiles) have somewhat ideal distribution of histogram, the big difference between the highest and the lowest histogram peak are reduced by a considerable degree. The scenario is illustrated in **Figure6**.CLAHE control the pixel value of the output image by clipping the highest histogram peaks and then equally redistribute the clipped pixels over the remaining gray-level ranges. Due to these advantages, CLAHE was selected for our purpose and all images were enhanced using this technique prior to feeding to the network.

The model was trained using the labeled image data after data augmentation. **Figure7**demonstrates the learning curve that illustrates the training and validation accuracy as well as loss of the Xception model. During model training, the state of the model at each epoch of the training algorithm have been evaluated using the training dataset. Evaluation using the validation dataset gives an idea of how well the model is generalized indicating the good fit of the model using loss of training and validation. Training loss and validation losses decreased to a point of stability with a small gap with the training loss.

In order to show the separability performance of diseases and to determine diseases that can be identified with high accuracy, the model was tested with separate datasets. As shown in Table 3 different classification accuracies, sensitivities and specificities have been achieved for all six classes. The model resulted less sensitivity for lung cancer (92.5%) and COPD (94.9%)compared to other classes. Highest sensitivity was achieved for TB (100%). Generally, the models over all classification accuracy, average sensitivity and average specificity were 97.3%, 97.2% and 99.4%, respectively. Our study presented improved accuracy and sensitivity for lung disease classification compared to related works[13,34-36]. This was achieved by using a model with very deep layers. Few techniques that claimed relatively better accuracy using deep learning based automatic detection algorithms are dedicate for pneumonia [13,16,14,15]or pulmonary tuberculosis[17,19,18]. However, the proposed methods have limited clinical application, as there are various pathologies and abnormalities other than pneumonia and pulmonary tuberculosis in real-world clinical practice.

In summary, this work presents a multi class classification algorithm for major five thoracic diseases that can be manifested on chest X-ray images using the state-of-the-art deep learning model. The developed GUI also allows user friendly implementation of the proposed system in clinical setting. The study could be extended to multi-label classification task from a single chest X-ray image. We were unable to do this because of unavailability of multi-disease labeled data.

5. CONCLUSION

This research employed the state-of-art Xception model of convolutional neural network for multiple lung disease classification task. Different image processing methods have been compared and implemented to enhance the quality of images prior to feeding to the model. Generally, using the Xception model over all classification accuracy of 97.3%, average sensitivity of 97.2% and average specificity 99.4% has been obtained. The system also allows capturing of images from paper X-ray images (films) in areas where only the conventional X-ray machines are available, as in the case of most remote health facilities of low resource settings. The proposed system can play a significant role in supporting radiologists and physicians during the diagnosis procedures by reducing the workload and diagnostic errors especially in developing countries where the means and the experts are in scarce.

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AUTHORS BIOGRAPHY

FethyaSeid received her BSc degree in Biomedical Engineering in 2017 and MSc in Biomedical Imaging in 2020 from the School of Biomedical Engineering, Jimma Institute of Technology, Jimma University, Ethiopia. She is currently working in Ethiopian drug and food supply agency of Ethiopia as a Biomedical Engineer.

Gizeaddis Lamesgin Simegn is an assistant professor in the school of Biomedical Engineering and chair of Biomedical Imaging program. He graduated from Jimma University with Bachelor of Science degree in Electrical Engineering in 2010, from Addis Ababa University with Master of Science degree in Biomedical Engineering in 2014 and from University of Cape Town with doctor of philosophy in Biomedical Engineering in 2019. His research interests include medical image processing and analysis, Bio signal processing, MRI pulse sequence programming, MRI image reconstruction and analysis and medical device and systems design.

Abel Worku Tessema had his first degree in Biomedical Engineering in 2015 and his M.Sc. in Biomedical Imaging in 2019. He is a currently a studying towards his PhD in Korea. He has been working as a lecturer and researcher at Jimma University, Jimma Institute of Technology, School of Biomedical Engineering since 2015. He is interested in researches related to medical image analysis and he has been engaged in different researches and won the first Grand Challenges Ethiopia seed grant competition in 2017.

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