Harla J. Eng. Tech. 2022 1(1): 18-40

Harla Journals

Harla Journal of Engineering and Technology

Journal home page: https://journals.ddu.edu.et/index.php/HJET

Harla journal of Engineering and Technology

Classification of Chronic Obstructive Pulmonary Diseases from Chest X-Ray Images Using Deep Learning

[1]Amanuel Meseret, [2]Kula Kakaba, [3]Tafary Kababa

[1]*Faculty of Computing and Informatics, Jimma Institution of technology Jimma University, Jimma, Ethiopia*

[2]*Faculty of Computing and Engendering, Addis Ababa Science & Technology, Addis Ababa, Ethiopia*

[3]*Faculty of Computing and Informatics, Jimma Institution of technology Jimma University, Jimma, Ethiopia*

[1]Amanuel Meseret : amanuelmeseret0@gmail.com

[2]Kula Kakaba : amanuelmeseret0@gmail.com

[3]Tafary Kababa : amanuelmeseret0@gmail.com

Abstract

The global Burden of Disease Study reports a prevalence of 251 million cases of COPD globally in 2016 and estimated that the Disease caused 3.17 million deaths. People in developing countries are highly at risk of the disease because they cannot get diagnosed early. In addition to this, they do not have enough experienced medical experts (radiologists). To contribute to the above severe problem, we investigated and developed an AI model that can classify sub-classes of COPD disease (asthma, Emphysema, and Chronic bronchitis). In the model development, we followed the design science methodology, which follows its scientific procedures starting from collecting the required data set to test the developed model. We have collected about 2248 images from local Hospitals, having 350 Images for each class. We have applied different image preprocessing Techniques to enhance the image. Therefore, to overcome that problem, we applied zooming, rotation, and flipping at different angles as augmentation techniques. Then Features are extracted from gray-level images using a CNN feature extraction. A classification model is built using 5 Different Pre-trained models called InceptionV3, VGG16, EffeceintNetB0, and Resnet50, including our own CNN model. The convolutional neural network architecture with the sequential model was implemented with many layers, such as convolutional, activation, and max-pooling, to extract essential features from the x-ray images. EffeceintNetB0 Accuracy was 85.7% test data, ResNet50 Model Accuracy was 67.5% on the test data, and VGG16 Accuracy was 87.6% on the test data also, our own CNN model obtained 81.1% on the test data. Experimental results show that the InceptionV3, with its filtering mechanism, has achieved a better classification performance with an accuracy of 90.1%.

Keywords: - *CNN - COPD-Deep learning, X-Ray, LMICs, Image Processing*

* Corresponding Author: Amanuel, amanuelmesert0@gmail.com
DOI:
© 2022 Harla Journals and Author(s). Published by Dire Dawa University on Open Access Policy under CC-BY-NC 4.0.
Manuscript received March, 2022; revised May, 2022; accepted June, 2022.

1. Introduction

diseases are the most common cause of these deaths. COPD is the leading cause of death worldwide, and the numbers are growing. Among the type of COPD, Asthma is the most common chronic disease, affecting about 21% of children globally, and rising and chronic bronchitis kill over 9.2 million worldwide also, 3.5 million people diagnosed with emphysema, with more than 90 percent of cases involving people over age 45 [3].

In lung disease diagnosis, clinicians integrate their medical knowledge and chest x-ray image to obtain the nature and pathological characteristics of lung diseases and to decide on treatment options. However, manual detection and classification of lung diseases in CXR, where a large number of CXR is taken for each patient, is tedious and subjected to inter-observer and intraobserver detection and classification variability [2].

Chronic obstructive pulmonary disease (COPD) is one of the most causes of death among patients of all ages especially for those older in major medical centers and hospitals in Ethiopia, chest radiographs are widely used in the detection and diagnosis of lung diseases. The main reason for automating the manual diagnosis is to overcome critical challenges that the radiologists face during the manual diagnosis like misdiagnosis of diseases due to a shortage of high-level expertise and the diagnosis procedure is time-consuming and tedious, Even in JUMC, there is only one expert radiologist to manage all imaging modalities. In addition to this, the occurrence of the disease is frequent enough in x-ray reports to provide a reasonable test set, and Chest radiography is an economical and easy-to-use medical imaging and diagnostic technique when compare with other imaging equipment like MRI and CT scan.

The great advantages of chest X-rays include their low cost and easy operation. Even in underdeveloped areas like Ethiopia, modern digital radiography (DR) machines are affordable. Therefore, that is why most hospitals and Health facilities use x-ray machines as common medical equipment to diagnose a disease.

1.2 Statement of the problem

Chronic obstructive pulmonary disease (COPD) is a problem in the lungs that prevents the lungs from working properly. The Global Burden of Disease Study reports a prevalence of 251 million cases of COPD globally in 2016 and Globally, it is estimated that 3.17 million deaths were caused by the disease in 2015 (that is, 5% of all deaths globally in that year) also More than 90% of COPD deaths occur in low- and middle-income countries since most of the cause is toxic effects of biomass fuel consumption, outdoor air pollution, tobacco smoke.[16] According to World Health Organization (WHO) estimated in 2011 that 34% of the Ethiopian population was affected by non-communicable diseases and dying by chronic obstructive pulmonary disease (COPD).

Similarly, Global Burden of Disease (GBD) studies estimated age-standardized death rates of 800 per 100,000 population for non-communicable diseases in Ethiopia, of which higher death rates (approximately 450 per 100,000) were attributed to cardiovascular disease and diabetes, 150 per 100,000 attributed to cancer, and 100 per 100,000 to chronic obstructive pulmonary disease [17]. These estimations were much higher than in many developed countries. Although these estimates of cardiovascular disease, cancer, diabetes mellitus, and chronic obstructive pulmonary disease look higher in Ethiopia, estimations by WHO and GBD studies are highly uncertain because the causes of death were predicted using cause-of-death models due to a lack of information on the level of mortality or cause of death at the country level, which should be substantiated by national pieces of evidence [18].

The reason that people in developing countries are highly at risk of the disease is that they cannot get diagnosed at the early stage of the disease. Accurate and effective detection of disease has great benefits to controlling and treating disease as fast as possible. Unfortunately, there is still a severe shortage of radiologists in our country since we are far below the target for the number of radiographers, with only 87 radiographers for the entire country compared to the HSDP III goal of 620. The HSDP III MTR does not provide specific data on radiologists. However, according to the AAU Radiology website, the nationwide radiologist to patient ratio is approximately 1:1,000,000. If this ratio is applied to the HSDP III MTR data, it implies a total of 60-80 radiologists for the entire country (Ethiopia) but there is only 25 senior radiology throughout the country. When we come to Jimma, there is only one radiology specialist for Jimma University Medical Center as well as private clinics. as a result, the diagnosis takes a long time, and also difficult to differentiate the Chronic obstructive pulmonary disease (COPD). This keeps many people from having the diagnosis at the right time and the treatment is also delayed. The delay of treatment leads to death. [19]

The extreme shortage of radiologists and allied professionals highlights the importance of teleradiology, especially since almost all radiologists live in urban areas. However, the FMOH recognizes that telemedicine can only partially address its physician manpower problem. The need for “homegrown” talent has been recognized. [20] Similarly, our chronic obstructive pulmonary disease classification model can support the radiologist by helping them during the Chest X-ray Image reading and interpretation (diagnoses)

In addition to the above reason, Medical errors are a leading cause of morbidity and mortality in the medical field and are substantial contributors to medical costs. [21] Radiologists play an integral role in the diagnosis and care of patients and, given that those in this field interpret 113,204 examinations annually in Ethiopia, this may contribute to diagnostic errors [24]. Errors can be categorized as a “miss” when a primary or critical finding is not observed or as a “misinterpretation” when errors in interpretation lead to an incorrect diagnosis. Recognizing the cognitive processes that radiologists use while interpreting images should improve one’s awareness of the inherent biases that can impact decision-making. [23] The automation will reduce common biases that impact clinical decisions, as well as strategies to counteract or minimize the potential for misdiagnosis. [22]

Previously most research has been conducted for many diseases from chest x-ray images using machine learning and Deep learning even for Chronic Obstructive pulmonary disease too. to solve the shortage and misdiagnosis of disease from chest x-ray but still, there wasn’t any researcher have investigated to classify subtype of Chronic Obstructive pulmonary disease so in this study we have taken the classification of subtype of Chronic obstructive pulmonary disease as a research Gap.

1.3 Related Work

Studies have been done using machine learning on two cascaded SVM classifiers [4] to classify the CXR image as TB and non-TB In this method, a small dataset has been used, to detect only TB from multiple lung diseases The result has relatively low accuracy (about 84%). Moreover, lung cancer and pneumonia detection using ANN were also proposed [5].

Even though the method detects both lung cancer and pneumonia diseases, with improved accuracy, it lacks further classification and the source of the data was not specified this will be less acceptable. And also, another method using Feedforward neural network [6] was also proposed to improve the accuracy and increase the classification of lung cancer, pneumonia, and TB, and they have used 1450 x-ray images but the source was not specified.

Recent state-of-the-art deep neural network (DNN) models have been used in many works for breast cancer diagnosis [38, 39]. To classify breast tissues biopsy images as normal, benign, malignant, and invasive carcinoma, a deep CNN-like patch level voting model and merging model were used and an accuracy of 87.5 % was achieved [70]. Likewise, DCNN and gradient boosted tree method was used to classify breast cancer into the basic 4 types [40] and an accuracy of 87.2 + 2.6% was reported.

CNN as a feature extractor and support vector machine as a classifier has been implemented in another study [41] by retrieving image information at different scales, including both nuclei and overall tissue organization. An accuracy of 77.8% for the four classes and 83.3% for carcinoma (in situ and invasive) or non-carcinoma (normal and benign) was claimed. The inception-v3 convolutional neural network has also been adapted and fine-tuned to make patch classification and majority voting was considered [42] for the whole slide classification yielding an accuracy of 85% over the four classes and 93% for non-cancer (normal and benign) versus malignant (in situ or invasive carcinoma) was reported. Similarly, SVM-based classification with texture features [7] was proposed to solve the problem related to the accuracy, it achieved 96%, the however further classification problems are still existing.

2. Materials And Methods

2.1 Data Annotating /Labeling

The Dataset was collected from 6 Hospitals Located in Ethiopia, Namely Jimma University Medical Center, MSF Holland Gambella Branch, St Paul's specialized Hospital, Balck Lion Specialized Hospital, and Reftyvally University college specialized hospital Adama Branch and Betele specialized Hospital and online datasets.

Also, professionals or experts from the 6 Hospitals (Jimma Medical Center, MSF Holland Gambella Branch, St.paul Specialized Hospital, Balck Lion Specialized Hospital, Rift valley University Collage specialized Hospital Adama, and Betel Specialized Hospital were involved in data annotation.

2.2 Preprocessing

2.4.1 Data Format Conversion

The main purpose of preprocessing is to convert the DICOM file (default extension for x-ray images) to a common image file (JPG). In CXR image analysis, Preprocessing will be done to enhance and remove noises from the image and to extract essential information for further image analysis. It includes Blur and focuses on corrections, Enhancements, Lighting corrections, filtering, noise removal and l, and Thresholding. Edge sharpening, and noise suppression.

2.4.2 Image Augmentation

Data augmentation is a process of increasing the number of training data points in a dataset by generating more data from the original dataset [26]. It is important to increase the number of datasets. It helps the network to learn more complex features from the data and prevent the problem of Over-fitting. In this study, various data augmentation techniques were performed on the original images dataset.

2.7 Implementation Tools

2.7.1 Python Programming language

I used python programming language because it offers concise and readable code. Whilst complex algorithms and flexible workflows stand at the back of deep learning and AI, Python's simplicity lets developers write dependable structures. Not only is this, Python code understandable by humans, but this also makes it easier to build models for machine learning.

2.7.2 OpenCV

I used an open computer vision module for the data (image) preprocessing (image conversion, contrast enhancement, edge sharpening, and noise suppression) because OpenCV is an open-source computer vision and machine learning software library.

2.7.3 Tensorflow and Keras

Keras is a high-level neural network API that is written in python which runs on top of Tensor-Flow or Theano or Microsoft Cognitive Toolkit (CNTK). It is very simple to develop a Model, user-friendly, easily extensible with python, and most importantly it contains pre-trained CNN models such as VGG16, Inception, EffeceintNetB0, and Resnet50 that we used during the experiment. It allows easy and fast prototyping and supports both CNN and ENN or the combination of the two [26].

2.7.4 Graphical Processing Unit (GPU)

We have used GPU as a standalone machine since this image processing work needs Graphics Card rather than just a CPU in order to overcome these issues we have used a GPU server offered by Google Company over the google colab notebook

2.7.5 Pre-Trained Model.

We used, VGG16, InceptionV3, EffeceinNetB0, and Resnet50 Pre-Trained Model to boost my Model Accuracy and to implement Transfer learning because the pre-trained models contain trained weights for the network.

2.8 Evaluation of Model

This experiment uses the F1 score and the accuracy to evaluate the performance of the model.

The metrics used to evaluate the model in this classification task are accuracy of classification accuracy (CA), precision, recall, and F1 score. Accuracy: - the model accuracy was calculated as the percentage of correct prediction of the top class (the class having the highest probability as indicated by the CNN model) and the target class will be assigned by the author beforehand is the same. It will be represented by the formula below,

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

2.8 Description of the proposed architecture

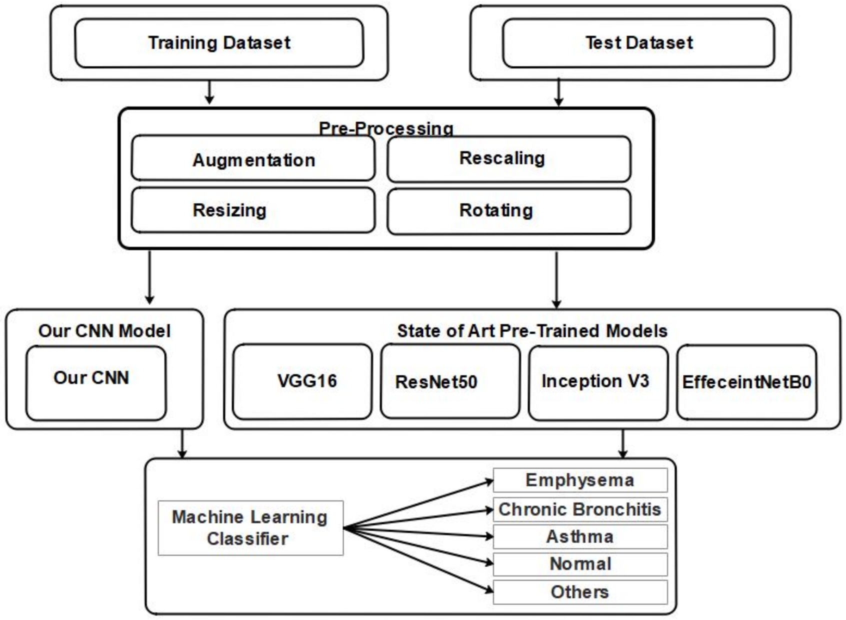

Figure 1 Proposed architecture

Code, Data, and Materials Availability[1,2]

3. Experiment and Discussion

3.1 Dataset preparation

We collected the data from four hospitals, namely Addis Ababa Tikur Anbesa specialized Hospital, st Paul's specialized Hospital, Betele Specialized Hospital, Jimma University Medical Center, and Reftyvally University College specialized hospital, and MSF Holland Gambella Branch. , After collecting those data from the selected hospital data augmentation was applied to the collected data to minimize the over-fitting problem and to increase the dataset size since CNN needs more data. The format of the collected images is DICOM (Digital Imaging and Communications in Medicine) which is .dcm files, but it is really difficult to work with Dicom image formats. Since it has low compression, it needs more memory to process and more computing time, so must be converted to JPEG (Joint Photographic Experts Group) format jpeg has great compression, for example, we try to convert the

[1] Source Code: https://github.com/Amanuel-Meseret/OHBD-Project/blob/master/Copy_of_Over_My_CNN_Arch.ipynb
[2] Dataset Link https://drive.google.com/drive/folders/1f-oLuMJTIWzTKD5y8jbZ99PH14aOo5m0?usp=sharing

images from DICOM format to JPEG, we used one of the .dcm images and realize that the size of (.dcm) is 15.5MB and the (.jpeg) is only 330KB, therefore jpeg has great compression. From the 2248 image data, 80% of the dataset was used for training and 20% was used for testing in our CNN Model also for the Pre-trained Model too.

Table 1 Source of Data

Sr No	Source of Images	No of Images	Type of Image	Image Format
1	Jimma University Medical Center	19	Emphysema and Asthma	JPEG
2	Reftyvally University collage specialized hospital	310	Asthma ,Chronic Bronchi’s and Emphysema	JPEG
3	St paul's specialized Hospital	422	Asthma ,Chronic Bronchi’s and Emphysema	JPEG
4	Addis Ababa Tikur Anbesa specialized Hospital	521	Asthma ,Chronic Bronchi’s and Emphysema	JPEG
5	Betele specialized Hospital	72	Asthma ,Chronic Bronchi’s and Emphysema	JPEG
6	MSF Holland Gambella Branch.	33	Asthma ,Chronic Bronchi’s and Emphysema	JPEG
	Online Dataset (Padchest)	871	Normal and Others	JPEG

Table 2 Data preparation

Class	Original collected images	Image format
Asthma	489	JPEG
Chronic bronchitis	338	JPEG
Emphysema	550	JPEG
Normal	510	JPEG
Others	361	JPEG

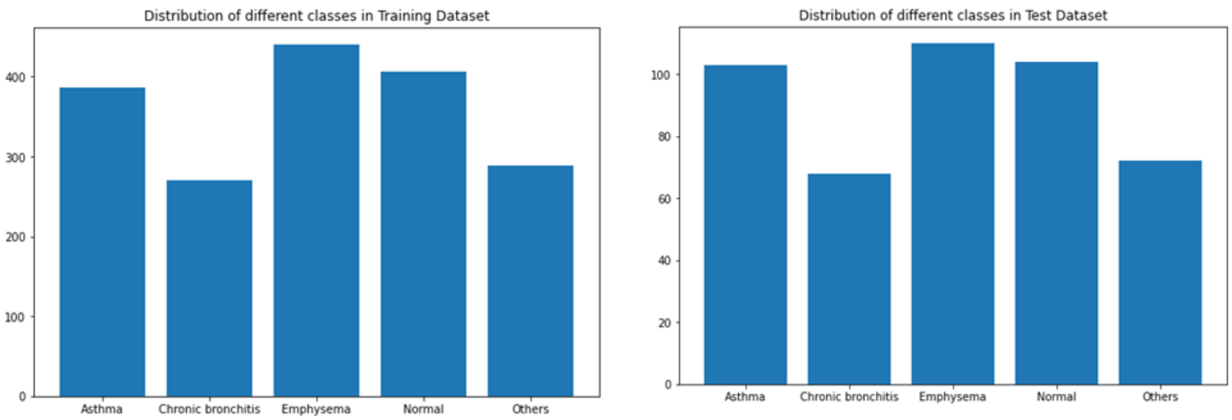

Figure 2 Data preparation

To implement the Chronic Obstructive Pulmonary Disease classification model, we make use of several open-source libraries. We used Google Collaborator 2021 with GPU for work with many open-source packages and libraries Google Collaborator 2021 is a distribution of the python programming languages for scientific computing (data science, machine learning application, large scale data processing, predictive analysis, etc.),

3.2 Hyper Parameters in the model

When training with our model, some hyperparameters determine the network structure for an optimized result of training. Those groups of hyperparameters are determined for the network according to several training data set by choosing the batch size. Those are the number of an epoch: it determines how many times the model reads all the data set, batch size: parts from all datasets to be highlighted at a time, number of iterations: the number of batches to finish the dataset in one epoch. And, the other group of hyperparameters is also the following that we discussed in chapter two, which may differ for different convolution layers to choose the best value of Parameters our data we have experiment little bit and the report is below

Table 3 Experimental Result of parameters Value

Sr No	*Batch Size*	*No of epoch*	*Learning Rate*	*Dropout Value*	*Number of Hidden Layer*	*Accuracy*	*Loss*

1	16	20	0.01	0.20	5	71.9%	0.655
2	16	20	0.01	0.40	5	66.5%	0.75
3	16	20	0.001	0.20	5	64.7%	0.81
4	16	20	0.001	0.40	5	66.0%	0.77
5	16	20	0.001	0.60	5	65.3%	0.79
6	16	20	0.0001	0.20	5	68.2%	0.75
7	16	20	0.0001	0.40	5	66.3%	0.80
8	32	20	0.01	0.20	5	68.6%	0.71
9	32	40	0.01	0.20	5	70.9%	0.66

After the experiment, we have got the hyper-parameters value that can give us the best performance for our model and it's described as below.

Table 4 Chosen CNN hyper-parameter Values

Hyper Parameter	Value
Activation	Relu
Striding	2
Padding	Same
Kernel size	3x3
Batch size	32
Learning rate	0.01
Dropout	0.2
Epoch	100
Optimizer	Adam

3.4 Evaluation result of Our Own CNN Model

In convolutional neural network model preparation, various parameters can influence the model performance. Therefore, we have to try to make optimum by assigning different values for those parameters, and finally, we have used a batch size of 32 because when the batch size is small the training time of the epoch is increased, epoch 100, optimizer "Adam" that is because adam is the best and suitable optimizer since it is the combination of Adgrad and RMSProp and we used grid search mechanisms to select this optimizer with 0.01 learning rate, dropout 0.2 to reduce model overfitting in the output 3 dense layers loss “categorical cross-validation” with the following model summary.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 222, 222, 16)      448
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 111, 111, 16)      0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 109, 109, 32)      4640
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 54, 54, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 52, 52, 64)        18496
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 50, 50, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 25, 25, 128)       0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 23, 23, 512)       590336
_________________________________________________________________
dropout (Dropout)            (None, 23, 23, 512)       0
_________________________________________________________________
flatten (Flatten)            (None, 270848)            0
_________________________________________________________________
dense (Dense)                (None, 512)               138674688
_________________________________________________________________
dense_1 (Dense)              (None, 512)               262656
_________________________________________________________________
dense_2 (Dense)              (None, 5)                 2565
=================================================================
Total params: 139,627,685
Trainable params: 139,627,685
Non-trainable params: 0
```

Figure 3: Summary of the model

Our CNN model trained using the different activation functions like sigmoid, Tanager, and Relu, but among those functions, Relu performs better accuracy. Also, we preprocessed the data using 224x224 image sizes by using BICUBIC interpolation resizing techniques.

In this experiment, the model was trained at the Test and training phase using a CNN filter with 224X224 image size and with Relu as an activation function. From this experiment, we have achieved 81.1% for training accuracy. In the training and Test curve, there is some gap between them; this is because the major drawback of the median filter is that all pixels are substituted by the median of the window even if the pixel under concern is uncorrupted.

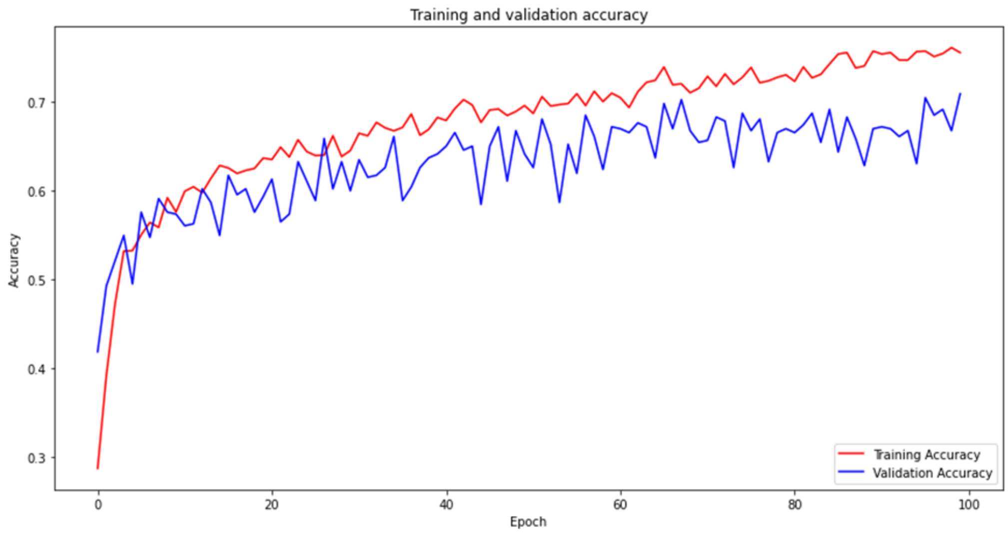

Figure 4 Training and Test Accuracy

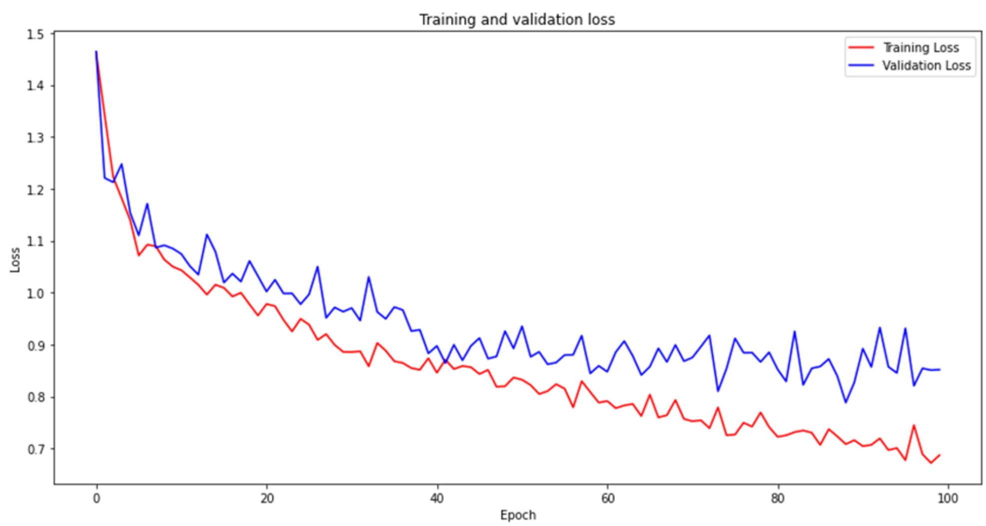

Figure 5 Training and Test Loss

The confusion matrix table of the softmax classifier in a convolutional neural network is shown in diagrams 46 and 47 we inferred from this testing that five classes (obstructive, non-obstructive, and others) were a little bit confused. That is, the best-verified outcome is postulated using a confusion matrix to show how our model is a little bit confused. As clearly depicted in figure 47 our model obtained 81.1% testing accuracy.

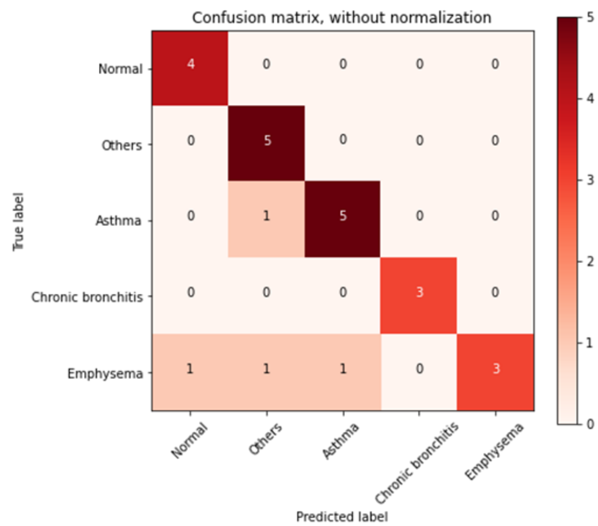

Figure 6 Confusion matrix

3.5 Evaluation result of InceptionV3 Pre-Trained Model

InceptionV3 is a pre-Trained Model of Google Brain and it has around 42 layers to perform the convolutions with different filter sizes on the input, performs Max Pooling, and concatenates the result for the next Inception module. Not only that, it introduced the 1 * 1 convolution operation to reduce parameters drastically and the model has only 7 million parameters. It was much smaller than the then prevalent models like VGG and Others Due to this, it takes only 3 hours and 32 minutes to train. In this experiment, the model was trained at the Test and training phase using Google Pre-Trained Model called Inception version 3 (InceptionV3) with 224X224 image size and with Relu as activation function. We have trained the model using 100 epochs and we have achieved 90.1% for Test accuracy respectively. This inceptionv3 model has high accuracy results on our test data. The Plot figure will show us the accuracy and loss result of the InceptionV3 model.

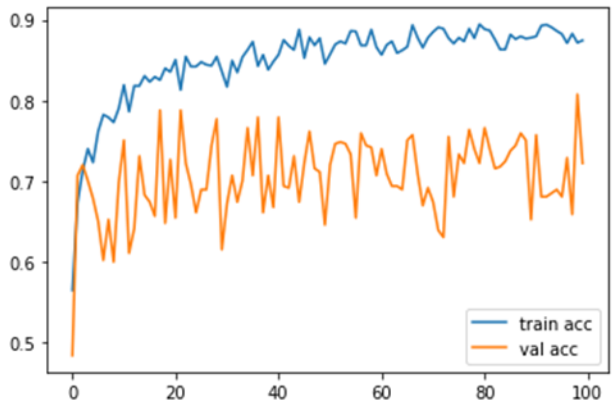

Figure 7 Loss of Training and Test

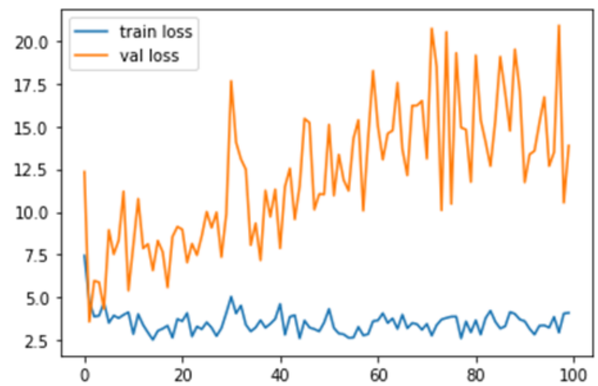

Figure 8 Training and Test Accuracy

3.6 Evaluation result of VGG16 Pre-Trained Model

VGG16 is one of the DCNN we have used in this work the architecture of VGG-16 is shown in Figure 51; it has 13 convolutional layers and 3 fully connected layers. The convolutional layers in VGG-16 are all 3×3 convolutional layers with a stride size of 1 and the same padding, and the pooling layers are all 2×2 pooling layers with a stride size of 2. The default input image size of VGG-16 is 224×224. After each pooling layer, the size of the feature map is reduced by half.

The last feature map before the fully connected layers is 7×7 with 512 channels and it is expanded into a vector with 25,088 (7×7×512) channels.

The default image size of VGG-16 was 224×224, which was the same as the size of the images in the dataset. We trained the model on the training data and tested the model on the test data (20% of the entire dataset) and the models' diagnostic efficiency of the test data. After 100 epochs (which took 4 hours and 45 minutes), we obtained 87.6% Test accuracy The Plot figure shows the accuracy and loss result of the VGG16 model.

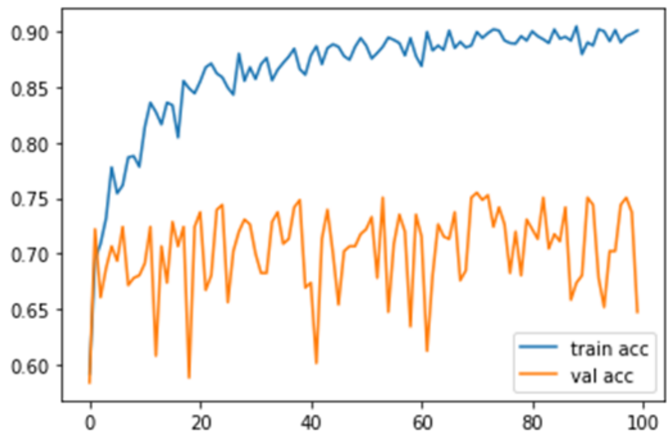

Figure 9 Training and Test Accuracy of VGG16

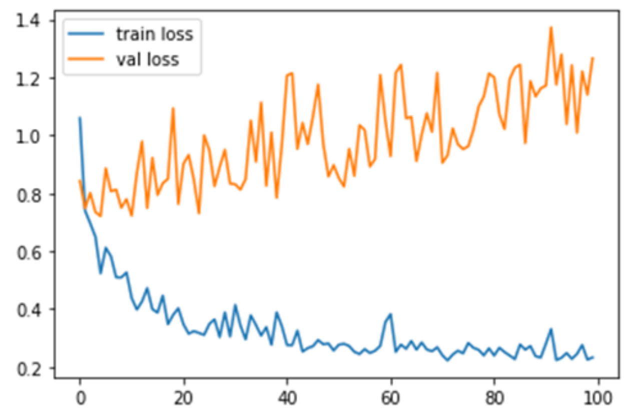

Figure 10 Loss of Training and Test of VGG16

3.7 Evaluation result of EffeceintNetB0 Pre-Trained Model

EfeceintNetB0 is the latest Model from In EfficientNetB0, Google proposes a new Scaling method called Compound Scaling. We achieve much better performance and we have gotten around 85.7% accuracy using constant parameters we have used in the previous models and it took around 3 hours and 55 Minutes for 100 epochs using Google GPU.

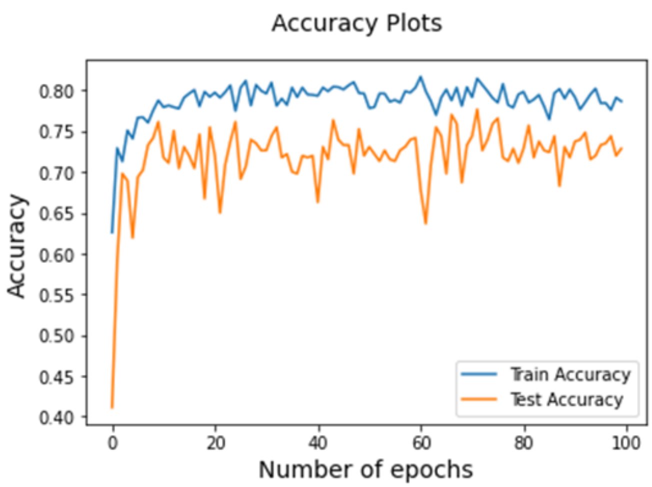

Figure 11 Training and Test Accuracy

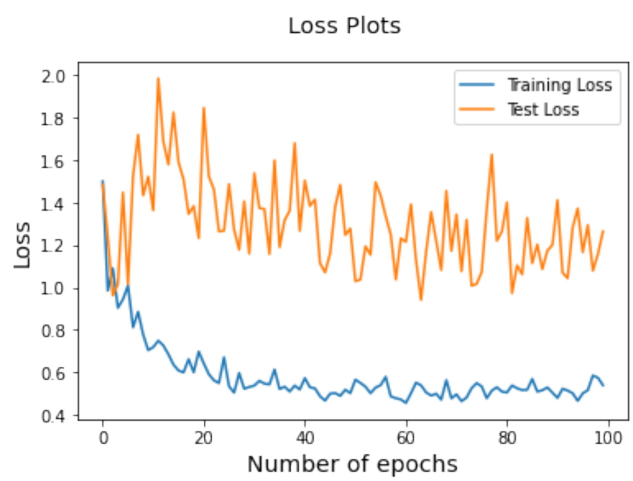

Figure 12 Loss of Training and Test

3.8 Evaluation result of ResNet50 Pre-Trained Model

The fourth DCCN Model is ResNet50 which has 50 Layers and 143,667,240 parameters with 224X224 image size and with Relu as an activation function. We have trained the model using 100 epochs.Because of the smaller dataset, we were unable to see the exact power of the Resnet50 model and the accuracy we have got is around 67.5% and it was reported as the smallest accuracy in this research. Compared with another DCCN model we have used in this work, we have got the smallest accuracy because Resnet50 is very vast and has bulky layers due to these issues it needs a big dataset but in our case, we have only 2,248 datasets for both training and test respectively.

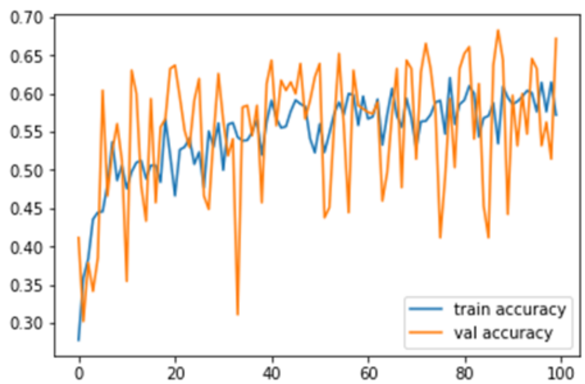

Figure 13 Training and Test Accuracy

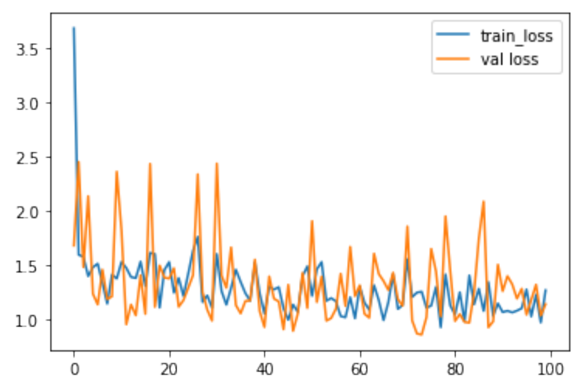

Figure 14 Loss of Training and Test

3.9 Discussion

We have collected 2248 images from different 4 health facilities and Online Dataset called Padchest we have distributed them to 8 health professionals (radiologists and medical doctors) to label images into 5 different classes namely Chronic Bronchi's, Emphysema, Asthma, Normal and Others among this 3 of them are a type of Chronic Obstructive pulmonary disease (COPD) we have used Normal Images (no Finding) to classify if the images are Normal then also we have collected non-COPD diseased images and named them as others so our model can classify if the x-ray images are COPD, non-COPD and even its Normal.

Data annotating part was very difficult and time-consuming it took about 2 months and a half to annotate 2248 x-ray images after the annotating step we have Categorized 489 images for Asthma, 338 images for Chronic bronchitis, 550 images for Emphysema, 510image for Normal, and 361images Others classes.

As Implementation environment, we have Google Collaborator because to train the images I need a Processor called Graphical Processing Unit which is available only on Servers and some few laptops called Gaming Computers so the only was using free only GPU services like Kaggle, Google Colab among them We have chosen the Google Collaborator because it has a very large community, tutorials and available free scripts, as main tensor flow open-source platform to build a CNN Network using its very powerful backend Keras and other libraries that makes the process very easy.

The common structure of a CNN for image classification has two main parts a long chain of convolutional layers for feature extraction and a few layers of the fully connected neural network for classification. For the feature extraction step, CNN with a sequential model with multiple layers is used. It consists of seven layers of Conv2D, with ReLu, Max-pooling2D, and fully connected layers. Then to classify Chronic Obstructive Pulmonary diseases, the extracted features are fed to dense layers. Features in the preprocessed dataset are extracted to reduce their dimension and use other Classification models like VGG16, Resnet50, InceptionV3, and EffeceintNetB0 on it. The convolutional neural network architecture with the sequential model is implemented with many layers such as convolutional, activation, max-pooling to extract important features from the Chronic Obstructive Pulmonary diseases x-ray image. Keras with the TensorFlow backend system helps to construct this model layer by layer. The Conv2D layer is used for input images as 2- dimensional matrices and a dense layer is used for output images. As a filter matrix, the kernel size was 3 x 3. As an activation function for this model ReLU was used. The size of the input images is (224, 224) for all and (299,299) only for Inception =V3. That means the height and weight of the images should be 224.

This research aims to create a different pre-trained model and compare it with my own CNN Model to do that I have chosen 4 pre-trained models one is the Google Pre-trained Model called InceptionV3, EffeceintNetB0, VGG16, and ResNet50 all of them has weighted the obtained from the imageNet large image dataset. First I have tried to train our Own CNN model but the accuracy was very small around 14% then I have experimented on hyperparameters values after many tries we have got the best value of parameters as Batch size 32, Dropout 0.20, learning rate 0.01, activation function Relu, kernel size 3X3, optimizer Adam epoch 100, there is one true while the number of epoch increase the accuracy also increase infect it time taking. Pooling layers reduce the number of parameters when the images are too large. Here MaxPooling2D of feature map matrix with stride value of 2 is applied to downsample the convolved image. We used MaxPooling2D because in practice this has been found to perform better than average pooling for image classification. It results in a downsampled or pooled feature map highlighting the most relevant feature in the patch. To find the probabilistic value, a flattening layer is used to convert the three-dimensionalities of an image to a single one, followed by two fully connected dense layers containing a SoftMax activation function for the highest likelihood classification.

The parameters used for compiling the CNN model are optimizer, loss, and metrics. As an optimizer, 'adam' has been used. It is a successful optimizer during the entire training to adjust the learning rate. For the loss function,' Categorical cross-entropy is used. The 'accuracy' metric is used to see the accuracy score on the validation set during the training of the model to make it even easier to interpret.

The 'fit ()' feature was used to train the CNN model. Since it is the most widely used in CNN applications, as we have described earlier we have used the 80/20 training/test ratio. The time () function is used to measure the time needed for the training. We have set the batch size and number of epochs in the fit function, which will loop the model through the data. The testing was processed after the training process had been completed to check the effectiveness of the trained CNN model. We have used our own CNN Architecture and four pre-trained models were used. Namely InceptionV3, VGG16, EffecientNetB0 and ResNet50.

In the beginning, we divided my dataset into 80% training and 20% test set then we uploaded it into Google Drive to Fitch them easily then we created the first CNN model and the accuracy was just only 14%.

Based on the value of the above parameter we have trained again the model then we obtained a very good result around 81.1% training accuracy. For the pre-trained models most of the parameters are already fine-tuned so we don’t need to alter or change values because the aim of using this pre-trained model to use their fined tuned layer, parameters value with weights they have obtained from the ImageNet.

The first pre-trained model we have trained is VGG16 which has around a 16-layer convolutional neural network to carry out the task. Image for the VGG16 transfer learning has been given as input to predict the object through Google drive in Google Colab.

And the trained took around 4 hours and 11 minutes then we obtained 87.6% training accuracy. The InceptionV3 uses 42 Layers and the concept For the InceptionV3 also followed the same approaches we have trained the last 3 dense layers among 42 Total layers and the concept of depth wise convolution method followed by a pointwise convolutional method to carry out the process. InceptionV3 model was invoked using Kera's framework Image for the Inception transfer learning has been given as input to predict the object through Google drive in Google Colab. And among 22,458,149 Total Parameters, we have trained only 655,365 which is 21,802,784 to implement the concept of Transfer learning and the trained took a little bit long time relative to the VGG16 because this model has a large size after the 5 hours and 32 minutes trained time we have obtained Very Good accuracy around 90.1%.

As a third model, we have used the EffeceintNetB0 Pre-trained model which was created by Google Company like Inception version 3 so the rest of the process is the same as VGG16 and Inception V3 but have trained a few of the last dense layers and we obtained 85.7% training accuracy.

Finally, we have used the ResNet50 which is the most very large pre-trained we have used in this work the reason why we need to experiment on is to see the effect of large CNN architecture on small dataset like us so the rest of the things keeps uniformly with others pre-trained model we have used unless we have used 23,534,592 parameters to train our data among 23,587,712 total of parameters ResNet50 has already, the result is so amazing we obtained only 67.5% training accuracy and it reported as the smallest accuracy in this work.

Table 5 Summary Table of Model Performance

Sr No	*Models*	*Trainable Parameters*	*Accuracy*
1	Our Own CNN Architecture	139,627,685	81.1%
2	InceptionV3	655,365	90.1%
3	VGG16	125,445	87.6%
4	EffeceintNetB0	325,445,21	85.7%
5	ResNet50	23,534,592	67.5%

4 Conclusion

Respiratory diseases cause a huge worldwide health burden, hundreds of millions of people suffer and, more than 1 million persons suffer from chronic respiratory conditions. At least 2 billion people are exposed to the toxic effects of biomass fuel consumption, 1 billion are exposed to outdoor air pollution and 1 billion are exposed to tobacco smoke. Each year, 4 million people die prematurely from chronic respiratory disease.

We have collected about 2248 images having 350 Images or more for each class. We have applied different image preprocessing tasks to enhance the image. And augmentation is applied to increase the number of images to a total of 2248 with approx. Therefore, to overcome that problem, we applied zooming, rotation, and flipping at a different angles as augmentation techniques. Then Features are extracted from gray-level images using a CNN feature extraction model then after we have extracted the features, the classification model is built using 4 Different Pre-trained models called InceptionV3, VGG16, EffeceintNetB0, and Resnet50 including our own CNN model.

We have used our own CNN Architecture and additional four pre-trained models were used. Namely InceptionV3, VGG16, EffecientNetB0 and ResNet50 and the Experimental results show that the InceptionV3 with its filtering mechanism has achieved a better classification performance with an accuracy of 90.1%.

6. Reference

[1] S. European Respiratory Society, Forum of International Respiratory Societies. Respiratory Diseases in the World. Realities of Today – Opportunities for Tomorrow. 2013.

[2] Helmberger M., Urschler M., Pienn M., Balint Z. "anatomy of lung.", ResearchGate, 2013.

[3] A. N. Zakirov, R. F. Kuleev, A. S. Timoshenko, and A. V Vladimirov, Advanced Approaches to Computer-Aided Detection of Thoracic Diseases on Chest X-Rays. vol. 9, no. 88, pp. 4361–4369, 2015.

[4] A. Karargyris et al., Combination of texture and shape features to detect pulmonary abnormalities in digital chest X-rays. Int. J. Comput. Assist. Radiol. Surg., vol. 11, no. 1, pp. 99–106, 2016.

[5] S. Pattar, Detection and Classification of Lung Disease – Pneumonia and Lung Cancer in Chest Radiology Using Artificial Neural Network, Int. J. Sci. Res. Publ., vol. 5, no. 1, pp. 2250–3153, 2015.

[6] E. Pune and V. I. T. Pune, Automatie Deteetion ofMajor Lung Diseases U sing Chest Radiographs and Classifieation by Feed-forward Artifieial Neural Network, pp. 1–5, 2016.

[7] G. P. Melendez and M. Cordel, Texture-based detection of lung pathology in chest radiographs using local binary patterns, BMEiCON 2015 - 8th Biomed. Eng. Int. Conf., 2016.

[9] C. Tataru, D. Yi, A. Shenoyas, and A. Ma, Deep Learning for abnormality detection in Chest X-Ray images, 2017.

[10] M. Haloi, K. R. Rajalakshmi, and P. Walia, Towards Radiologist-Level Accurate Deep Learning System for Pulmonary Screening, 2018.

[13] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers, ChestX-ray8: Hospital- scale chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases,Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017, vol. 2017–Janua, pp. 3462–3471, 2017.

[14] H. Wang and Y. Xia, ChestNet: A Deep Neural Network for Classification of Thoracic Diseases on Chest Radiography, pp. 1–8, 2018.

[16] WHO Global Health Estimates 21 June 2021, https://www.who.int/news-room/fact-sheets/detail/chronic-obstructive-pulmonary-disease-(copd)

[17]. Abegunde DO, Mathers CD, Adam T, Ortegon M, Strong K. The burden and costs of chronic diseases in low-income and middle-income countries. Lancet. 2007;370:1929–38. [PubMed] [Google Scholar]

[18] Tesfaye F, Byass P, Wall S. Population based prevalence of high blood pressure among adults in Addis Ababa: uncovering a silent epidemic. BMC Cardiovasc Disord. 2009;9:39. doi: 10.1186/1471-2261-9-39. [PMC free article] [PubMed] [Google Scholar]

[19] HSDP III mid-term review [homepage on the Internet]. [Cited 9/26/2009]. Available from: http://www.moh.gov.et/index.php?option=com_remository&Itemid=0&func=fileinfo&id =5

[20] Center for national health development in Ethiopia [homepage on the Internet]. [Cited 9/26/2009]. Available from: http://cnhde.ei.columbia.edu/programs/hep/index.html

[21] Ray Sipherd, June 10, 2021 https://www.cnbc.com/2018/02/22/medical-errors-third-leading-cause-of-death-in-america.html#:~:text=A%20recent%20Johns%20Hopkins%20study,after%20heart%20disease%20and%20cancer.

[22] Brady A. P. (2017). Error and discrepancy in radiology: inevitable or avoidable?. Insights into imaging, 8(1), 171–182. https://doi.org/10.1007/s13244-016-0534-1

[23] Busby LP, Courtier JL, Glastonbury CM. Bias in Radiology: The How and Why of Misses and Misinterpretations. Radiographics. 2018 Jan-Feb; 38(1):236-247. doi: 10.1148/rg.2018170107. Epub 2017 Dec 1. PMID: 29194009; PMCID: PMC5790309.

[24] Shimelis D, Atnafu A. Status of radiological services in Addis Ababa public hospitals. Ethiop Med J. 2011 Jul; 49(3):257-63. Erratum in: Ethiop Med J. 2011 Oct; 49(4):377. Tsige, Mesfin [corrected to Shimelis, Dagmawit]. PMID: 21991759.

[26] Haykin, S. (2009). Neural Networks and Learning Machines (3rd Ed.). Pearson Education, Inc.

[38], Z. Han, B. Wei, Y. Zheng, Y. Yin, K. Li, and S. Li, “Breast Cancer Multi-classification from Histopathological Images with Structured Deep Learning Model,” Sci. Rep., vol. 7, no. 1, pp. 1–10, 2017

[39] Y. Guo, H. Dong, F. Song, C. Zhu, and J. Liu, “Breast Cancer Histology Image Classification Based on Deep Neural Networks,” in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2018, vol. 10882 LNCS, pp. 827–836.

[40] A. Rakhlin, A. Shvets, V. Iglovikov, and A. A. Kalinin, “Deep Convolutional Neural Networks for Breast Cancer Histology Image Analysis,” Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 10882 LNCS, pp. 737–744, 2018.

[41] T. Araujo et al., “Classification of breast cancer histology images using convolutional neural networks,” PLoS One, vol. 12, no. 6, pp. 1–14, 2017.

[42] A. Golatkar, D. Anand, and A. Sethi, “Classification of Breast Cancer Histology Using Deep

[43] Ivy Wigmore, June 12, 2021, https://whatis.techtarget.com/definition/data-labeling

[44] AWS of Amazon, June 11, 2021, https://aws.amazon.com/sagemaker/groundtruth/what-is-data-labeling/

[65], Yimer, Fethyaseid & Tessema , Abel & Simegn , Gizeaddis. (2021). Multiple Lung Diseases Classification from Chest X-Ray Images using Deep Learning approach. International Journal of Advanced Trends in Computer Science and Engineering.

Harla Journal of Engineering and Technology gives access to this work open access and licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.
(Creative Commons Attribution-NonCommercial 4.0 International License)