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THORAX DISEASE DETECTION USING X-RAY

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Abstract **-** This paper deals with the idea of development of this new deep learning algorithm suitable for predicting lung diseases from x-ray images. The technology may be able to read and process extremely large amounts of scans. The study of using different deep learning for detection of various thoracic diseases has been an active and challenging research area. Patients suffering from thoracic diseases need to take Chest X-Rays which are studied by radiologists and a report is generated by them. However, today with the increase in the number of thoracic patients in developing countries like India, a quick method to classify the disease and generate the report has become necessary. Also, a patient record has to be considered for diagnosis. The algorithm which is used in this paper offers a comparative study on the various deep learning techniques that can process chest X-rays and are capable of detecting the different thoracic diseases. Also, this algorithm has been proposed to classify 14 diseases namely Atelectasis, Cardiomegaly, Consolidation, Edema, Effusion, Emphysema, Fibrosis, Hernia, Infiltration, Mass, Nodule, Pneumonia, Pneumothorax, Pleural thickening and one for no disease based on the given X-rays using Convolutional Neural Network.

Index Terms **- Deep Learning, Data Set, Tensor Flow, Accuracy, CNN, X-Ray, Neural Network**

I. INTRODUCTION

Chest diseases are one of the most critical health problems people experience in the world. More than 0.92 million adults with pneumonia are hospitalized, with about 5000 dying each year in India alone. Chest x-ray images are the most general tool used to diagnose chest diseases, since their devices, in addition to making the patient exposed to little radiation, are also fairly low budget. Depending on the world health organization count, about two-thirds of the planet's community suffers from a lack of entry to radiation diagnosis. Even with the accessibility of the indispensable equipment for radiography, the experts who are able to interpret the x-rays are few, especially in the countryside, leading to an increase in the mortality rate of treatable diseases in many countries. So initial recognition and treatment should be available to prevent complications of pneumonia that may lead to death. Studying and distinguishing Chest X-ray images may be an entry-level task for radiologists but, in fact it is a compounded reasoning problem which often requires thoughtful review and good knowledge of anatomical principles, physiology and pathology. Such factors increase the obstacles of developing a consistent and automated technique for reading chest X-ray images while simultaneously considering all common thoracic diseases.

The thorax, also called chest, is the upper part of the trunk located between the neck and the abdomen. It gets support from the rib cage, the girdle of the shoulder and the spine that also protects it. It is the region of the body formed by the sternum, the thoracic vertebrae, and the ribs. It resides between the neck and diaphragm excluding the upper limb. The heart and lungs reside in the thoracic cavity, as well as many blood vessels which play a vital role in feeding (oesophagus), breathing, and pumping the blood to all parts of the body.

Chest pain is the most frequent reason for consultation and emergency room visits. Chest radiography is the most common imaging examination globally, critical for screening, diagnosis, and management of many life threatening thoracic diseases. Today, knowledge and observation skills of radiologists are imperative to read CXRs. However, the pathologies have complex structures, and the lesions in images of the lungs have very slight differences wherein some miniscule details can be missed out by experts. Also, there is a lack of trained and expert radiologists. Hence, in modernistic years there has been a lot of experimentation to develop systems that can remark on thoracic diseases as well as initiate reports.

II. SOFTWARE DESCRIPTION

(A) Jupyter Notebook: Jupyter Notebook is an IDE that provides us with an easy-to-use, interactive data science environment across many programming languages.

(B) Keras: Keras provides a python interface for artificial neural networks.

(C) Tensorflow: TensorFlow is an end-to-end open source platform for machine learning. It helps in building ML models easily using high level APIs.

(D) Python: Python is a programming language. Which has easy syntaxes to read that allows fewer lines of code to the programmers.

This language is also suitable for other customized applications.

(E) OpenCV: OpenCV (Open Source Computer Vision Library) is a programming library consisting of functions mainly aimed towards real-time computer vision and is developed by Intel, it had been supported by Willow Garage then Itseez (later acquired by Intel). The library is cross-platform and free to be used under the open-source BSD license.

(F) TKinter: TKinter is a framework that is used to create GUI applications easily.

(G) Pillow: Pillow is a python library that is used to add image processing capability to the python interpreter.

III IMPLEMENTATION OF THE PROPOSED SYSTEM

3.1 Dataset

The dataset of the proposed system has been taken from the kaggle repository. In this dataset, there is a csv file and 5606 images and the resolution of each image is 1024*1024. To create these labels, the authors used Natural Language Processing to text-mine disease classifications from the associated radiological reports.The image labels are NLP extracted so there could be some erroneous labels but the NLP labeling accuracy is estimated to be > 90%.

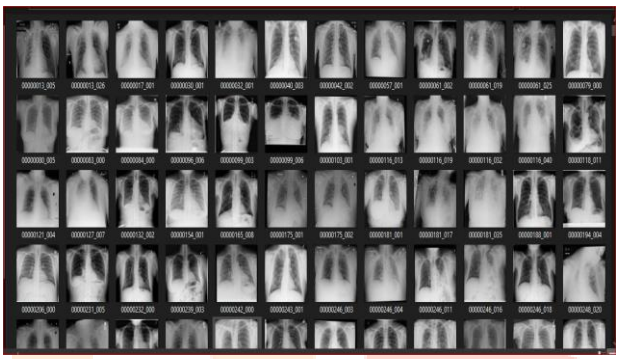

Fig. 1: images in dataset

There are 15 classes (one is “No findings” and another 14 diseases) in the our dataset, but this dataset is 5% of the nih x-ray dataset, various classes are scarce marked as “No findings”: Atelectasis - 508 images, Pneumonia-62 images, Hernia-13 images, Edema-118 images, Emphysema-127 images, Cardiomegaly-141 images, Fibrosis-84 images, Pneumothorax-271 images, Consolidation-226 images, Pleural Thickening-176 images, Mass 284 images, Effusion - 644 images, Infiltration 967 images, Nodule-313 images, No Finding - 3044 images.

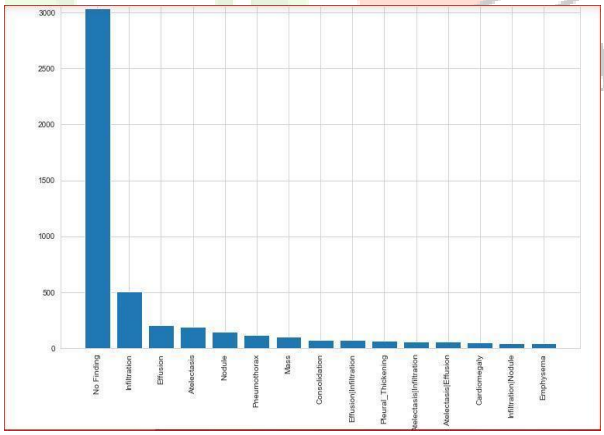

Fig. 2: number of images of different disease

We have a csv file (sample.csv) which consists of the following column -

- Image Index: File name
- Finding Labels: Disease type (Class label)
- Follow-up #
- Patient ID
- Patient Age
- Patient Gender
- View Position: X-ray orientation
- OriginalImageWidth
- OriginalImageHeight
- OriginalImagePixelSpacing_x
- Original Image Pixel Spacing y

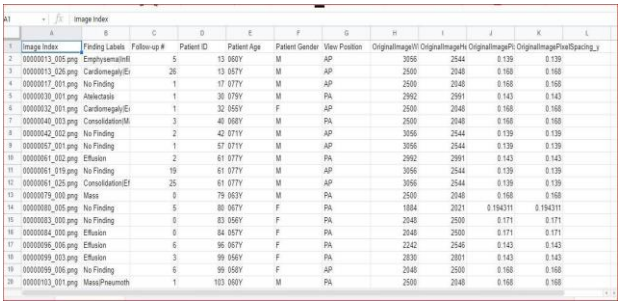

Image Index	Finding Labels	Follow-up #	Patient ID	Patient Age	Patient Gender	View Position	OriginalImageWi	OriginalImageHe	OriginalImagePi	OriginalImagePixelSpacing_y
00000013_005.png	Emphysema|Infi	5	13	060Y	M	AP	3056	2544	0.139	0.139
00000013_026.png	Cardiomegaly|Ei	26	13	057Y	M	AP	2500	2048	0.168	0.168
00000017_001.png	No Finding	1	17	077Y	M	AP	2500	2048	0.168	0.168
00000030_001.png	Atelectasis	1	30	079Y	M	PA	2992	2991	0.143	0.143
00000032_001.png	Cardiomegaly|Ei	1	32	055Y	F	AP	2500	2048	0.168	0.168
00000040_003.png	Consolidation|M	3	40	068Y	M	PA	2500	2048	0.168	0.168
00000042_002.png	No Finding	2	42	071Y	M	AP	3056	2544	0.139	0.139
00000057_001.png	No Finding	1	57	071Y	M	AP	3056	2544	0.139	0.139
00000061_002.png	Effusion	2	61	077Y	M	PA	2992	2991	0.143	0.143
00000061_019.png	No Finding	19	61	077Y	M	AP	3056	2544	0.139	0.139
00000061_025.png	Consolidation|Ef	25	61	077Y	M	AP	3056	2544	0.139	0.139
00000079_000.png	Mass	0	79	063Y	M	PA	2500	2048	0.168	0.168
00000080_005.png	No Finding	5	80	067Y	F	PA	1804	2021	0.194311	0.194311
00000083_000.png	No Finding	0	83	056Y	F	PA	2048	2500	0.171	0.171
00000084_000.png	Effusion	0	84	057Y	F	PA	2048	2500	0.171	0.171
00000096_006.png	Effusion	6	96	067Y	F	PA	2242	2546	0.143	0.143
00000099_003.png	Effusion	3	99	056Y	F	PA	2830	2801	0.143	0.143
00000099_006.png	No Finding	6	99	058Y	F	AP	2048	2500	0.168	0.168
00000103_001.png	Mass|Pneumoth	1	103	060Y	M	PA	2500	2048	0.168	0.168

Fig. 3: sample.csv

3.2 Data Preprocessing

The size of the original image is 1024*1024. This size is very large so we need to rescale the size of image to 400*400 for a better and faster training stage.

Fig. 4: original image of size to 1024*1024

Fig. 5: image resized to 400*400

We have used seaborn library to plot boxplot to check for outliers and then found that there was one outlier in patient age in our dataset so we remove it so that we don't have any disproportionate effect on our result.

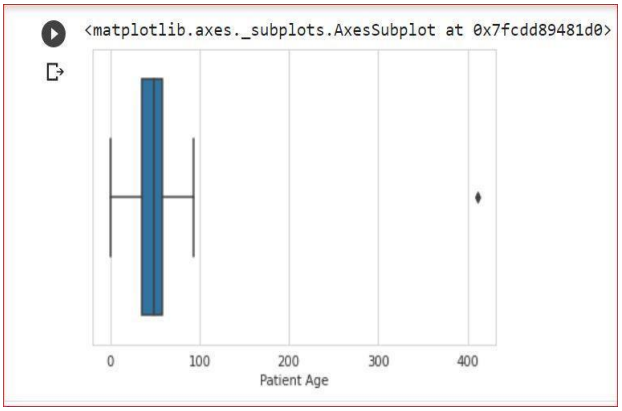

Fig. 6: checking for outliers

We then checked for any gender biased data, we inferred that Consolidation and Pneumothorax cases were seen in females rather than in males. While Atelectasis affected males more than females of same ages.

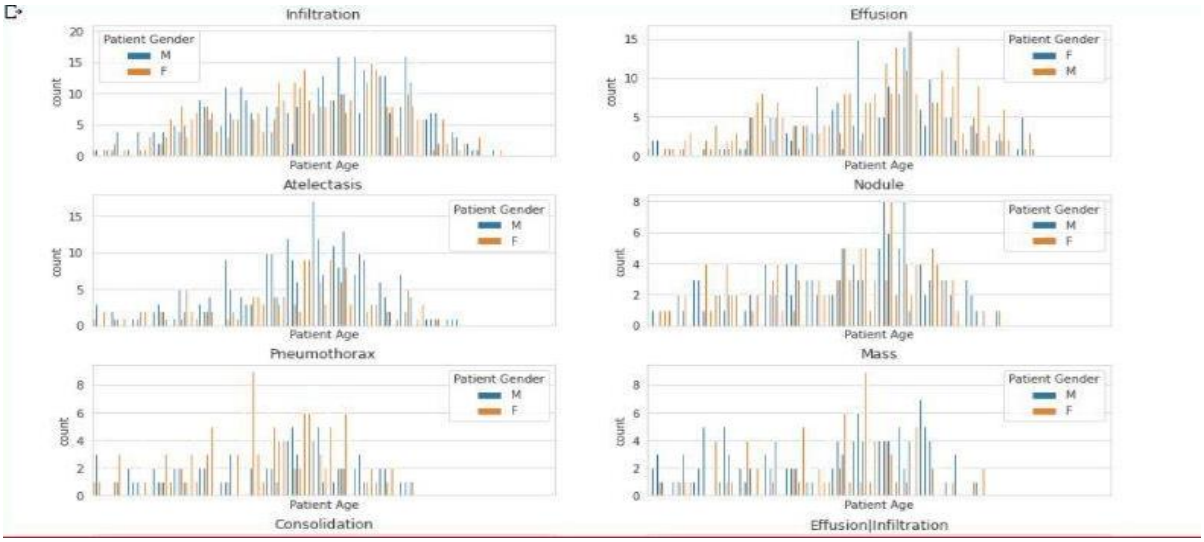

Fig. 7: graph plotted between age affected patients of different gender for different diseases

We also conjectured that more than 75% patients of Effusion or Cardiomegaly showed signs of multiple pathologies in their x-ray reports. Also it is more likely for a thorax disease sufferer to have more than one disease.

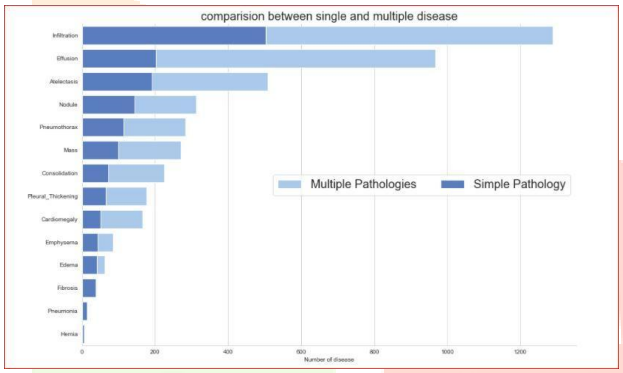

Fig. 8 :comparison between simple and multiple disease

3.3 Data Augmentation

We have performed horizontal, vertical, flipping, and rotational augmentation to increase the size and introduce variability in our dataset.

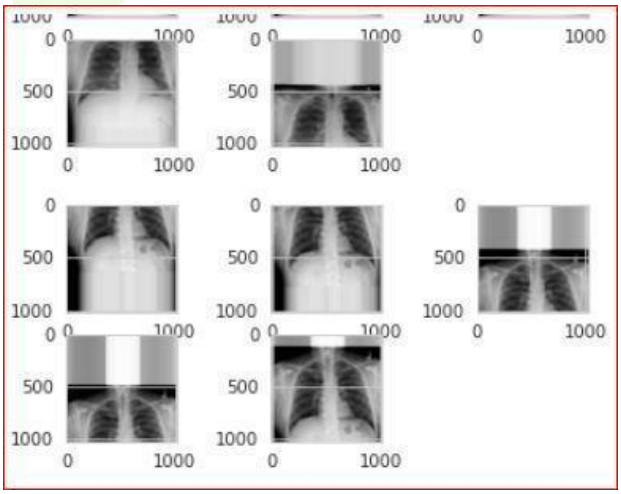

Fig. 9: augmentation

3.3 Model

After preprocessing we split our data into train dataset and test dataset. Our train dataset consists of 80% of our dataset and test data consist of 20% of the whole dataset.

Then we apply Convolutional Neural Network for Image Classification on our train and test dataset. The features of the images will be extracted using a deep convolutional neural network model consisting of convolutional layers, ReLU activation, Softmax activation and dropouts. The final layer will be a fully connected layer with output features corresponding to the number of classes which will help in classifying the image i.e predicting the disease label.

We set our initial epoch count to 0 and train our model until the epoch count equals 100. After getting the appropriate accuracy we save our model and then this saved model is deployed using tkinter.

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 400, 400, 1)]	0
conv2d (Conv2D)	(None, 199, 199, 32)	320
conv2d_1 (Conv2D)	(None, 99, 99, 64)	18496
conv2d_2 (Conv2D)	(None, 49, 49, 128)	73856
conv2d_3 (Conv2D)	(None, 24, 24, 256)	295168
conv2d_4 (Conv2D)	(None, 11, 11, 512)	1180160
flatten (Flatten)	(None, 61952)	0
dropout (Dropout)	(None, 61952)	0
dense (Dense)	(None, 256)	15859968
dropout_1 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 64)	16448
dropout_2 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 15)	975

Fig. 10 : model summary

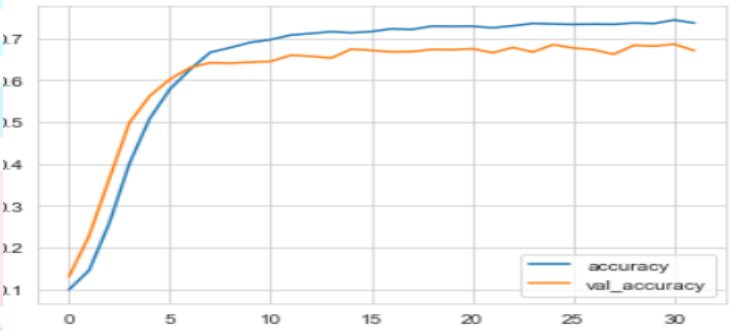

Fig. 11 : accuracy vs validation accuracy Graph

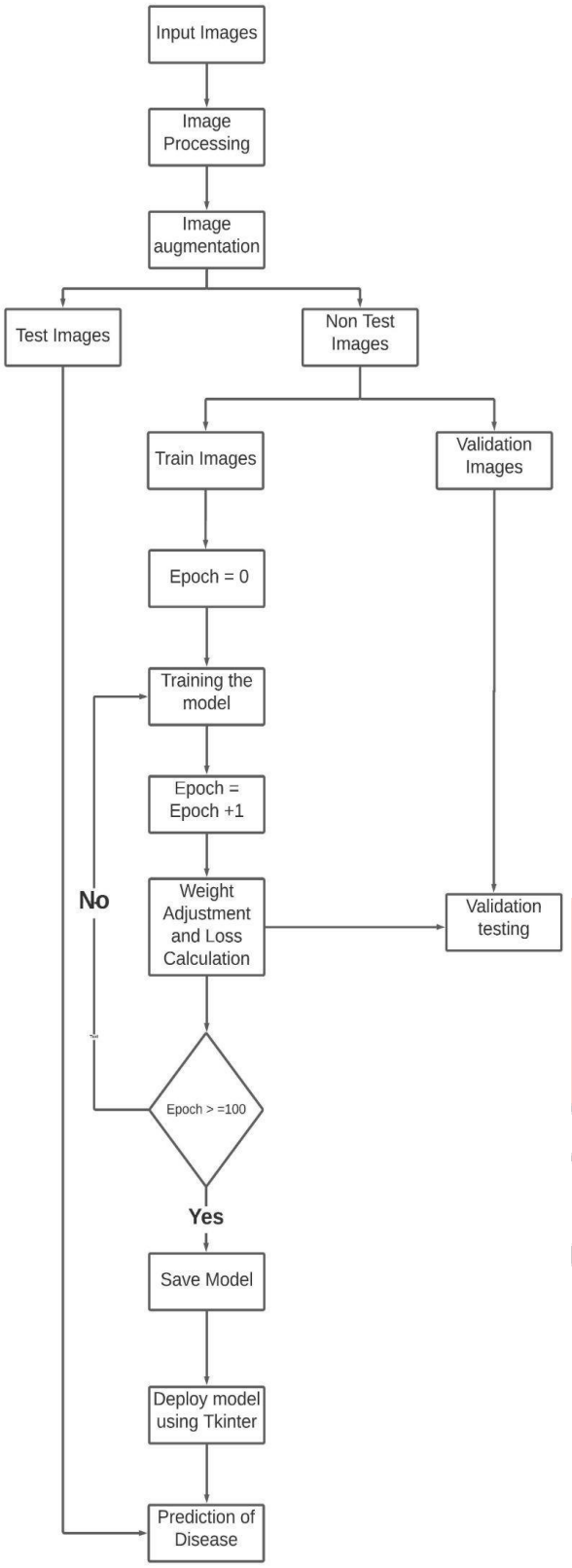

Fig. 12 : Working of our proposed system

III. RESULT

Step 1:

We have created a GUI which provides users a medium to interact with our created model. It has an upload image option which will be used to upload different X-ray images by browsing the user .

Fig 13 : GUI interface

Step 2:

When we click on the upload image option, a browsing window on the user system will open to select an image, now we can select any X-ray image for which we have to predict the result.

Fig 14 : uploading image in interface

Step 3:

After uploading the image, the GUI will display the predicted disease. In this case we selected an X-ray Image that has Effusion disease and we get predicted output as X-ray has Effusion disease.

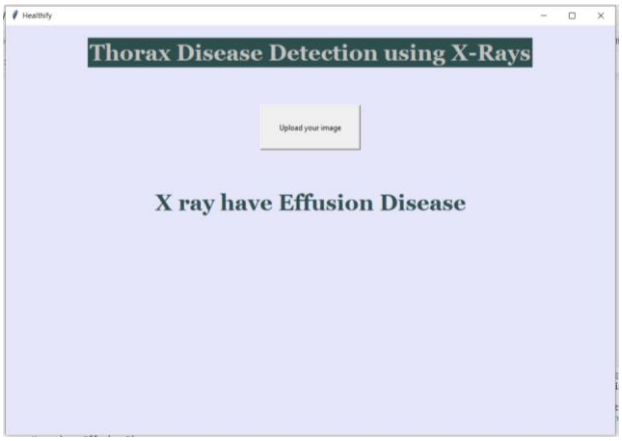

Fig 15: predicted output

V. CONCLUSION

The use of deep learning techniques in the field of Detecting thoracic diseases from chest x-rays is still an active area of research. Hence timely diagnosis is critical. With the help of deep learning, faster and quicker diagnosis of thoracic diseases could save time. From the comparative study, the different methods used to process chest x-rays as well as detect the thoracic diseases was understood. As future works a website can be made so that more users can access this model easily and get benefited. In addition, it will be extended to cover more disease classes and integrated with other clinical information, e.g., followup studies across time and patient history.

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