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DETECTION OF ABNORMALITIES FROM CHEST RADIOGRAPHS USING DEEP LEARNING

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Abstract—*The motivation towards this project comes from the fact that it would help medical professionals in evaluating a chest radiograph, as reading a radiograph correctly comes with experience. Our model will help experienced as well as inexperienced practitioners in overcoming the ambiguity encountered in evaluating radiographs and be of special use in remote regions.*

This paper examines the construction of an automated system for detecting the abnormalities present in chest radiographs, which could prove beneficial to the medical professionals in evaluating the disease(s) associated with a chest radiograph. This system is constructed using Deep Learning, in which the model learns to detect 14 classes of diseases using the training dataset and provides a graphical user interface which outputs a patient report.

Key Words—Deep learning, Image classification, Chest x-ray image, Convolutional neural network (CNN), Multi-label classification, Graphical user interface (GUI).

1. INTRODUCTION

It was revealed during a discussion with a doctor who has been practicing for over 25 years in the field, that at a given time she may read an X-ray and conclude that the patient is suffering from say x disease but, if she read the same X-ray after sometime she may conclude that the patient is not suffering from x disease but y disease. Our model is meant to help experienced and inexperienced practitioners in overcoming this ambiguity and producing consistent results.

We propose a model based on convolutional neural network to perform multi-label classification on 14 most prominent abnormalities present in patient's chest radiograph. Also, a GUI paired with this model along with a report generator, for user friendly interaction between medical practitioner and the trained model.

2. BACKGROUND

Table -1: Chexpert dataset distribution

Pathology	Positive (%)	Uncertain (%)	Negative (%)
No Finding	16627(8.86)	0(0.0)	171014(91.14)
Enlarged Cardiom.	9020(4.81)	10148(5.41)	168473(89.78)
Cardiomegaly	23002(12.26)	6597(3.52)	158042(84.23)
Lung Lesion	6856(3.65)	1071(0.57)	179714(95.78)
Lung Opacity	92669(49.39)	4341(2.31)	90631(48.3)
Edema	48905(26.06)	11571(6.17)	127165(67.77)
Consolidation	12730(6.78)	23976(12.78)	150935(80.44)
Pneumonia	4576(2.44)	15658(8.34)	167407(89.2)
Atelectasis	29333(15.63)	29377(15.66)	128931(68.71)
Pneumothorax	17313(9.23)	2663(1.42)	167665(89.3)
Pleural Effusion	75696(40.34)	9419(5.02)	102526(54.64)
Pleural Other	2441(1.3)	1771(0.94)	183429(97.76)
Fracture	7270(3.87)	484(0.26)	179887(95.87)
Support Devices	105831(56.4)	898(0.48)	80912(43.12)

This project largely revolves around the dataset provided by IRVIN and RAJPURKAR Et Al. The dataset consists 224,316 chest radiographs of 65,240 patients[1]. It is labelled as Positive, Negative, and Uncertain (blank for unmentioned, 0 for negative, -1 for uncertain, and 1 for positive) as shown in the table above.

We also use the dataset provided by MIT. The dataset consists 377,110 chest radiographs from 227,827 imaging studies[2]. It is labelled as Positive, Negative, and Uncertain (blank for unmentioned, 0 for negative, -1 for uncertain and 1 for positive) as shown in the table below.

Table -2: MIMIC-CXR-JPG dataset distribution

Pathology	Positive(%)	Uncertain(%)	Negative(%)
No Finding	75163(100.0)	-	-
Enlarged Cardiom.	7004(32.5)	9307(43.12)	5271(24.42)
Cardiomegaly	39094(64.22)	5924(9.73)	15860(26.05)
Lung Lesion	6129(76.69)	1020(12.76)	842(10.53)
Lung Opacity	50916(91.09)	2110(3.78)	2868(5.13)
Edema	26455(41.65)	11781(18.55)	25246(39.76)
Consolidation	10487(48.90)	3022(14.09)	7939(37.02)
Pneumonia	15769(27.30)	17789(30.80)	24205(41.90)
Atelectasis	45088(80.62)	9897(17.69)	937(1.76)
Pneumothorax	9317(17.73)	868(1.65)	42335(80.60)
Pleural Effusion	53188(62.13)	5345(6.24)	27072(31.62)
Pleural Other	1961(69.81)	728(25.91)	120(4.27)
Fracture	3768(76.16)	299(6.04)	880(17.78)
Support Devices	65637(95.39)	96(0.13)	3070(4.46)

3. MODEL SELECTION

3.1 Data conditioning

Initially, the datasets were combined, and split into a 72:18:10 train-validation-test split. The results obtained from this model proved to be highly unsatisfactory. This was due to the highly imbalanced nature of the dataset. Therefore, conditioning was required where-in the classes (Positive and Negative) needed to be balanced in some manner.
It was decided to implement over-sampling and under-sampling of the dataset with respect to the classes.

Another approach taken was to train a separate model with just the certain labels and to predict the uncertain labels followed by retraining the entire model with the certain as well as the new relabelled previously uncertain labels.

Through interactions with medical professionals and work by [1] we were made aware of the existence of a Pathology hierarchy into which the 14 abnormalities conformed.

Therefore, the labels of the dataset were conditioned in such a way that

- The uncertain labels were made positive so as to increase the sensitivity of the model
- The labels conformed to the Pathology hierarchy Fig.1.which they did not initially.

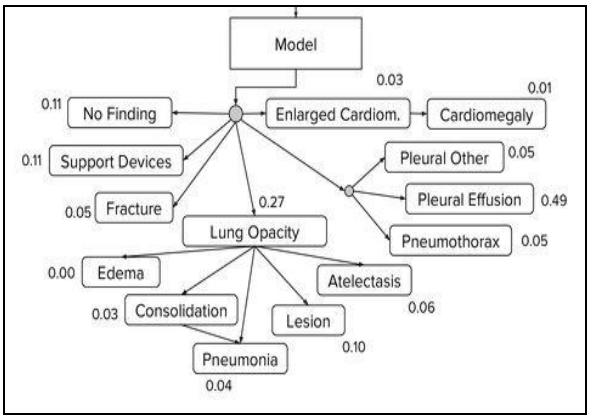


Fig -1: Pathology hierarchy as in [1]

3.2 Model performance

As mentioned above, the initial model produced unsatisfactory results. Therefore, the next course of action was to implement models which were trained on datasets that were sampled using the over-sampling and under-sampling techniques. According to the over-sampling technique the Minority class (positive) samples were duplicated so as to equate their numbers to that of the Majority class (negative).The under-sampling technique involved randomly deleting samples from the Majority class (negative) so as to equate their numbers to the minority class (positive).

The results of the models using these 2 techniques were unsatisfactory and also the over-sampling technique required a large training time and under-sampling technique discarded a lot of important data samples.

These unsatisfactory results were realised to be caused due to the data not conforming to the Pathology hierarchy. Therefore, on conditioning the data, a model was trained till the training loss plateaued (model overfit). Next, this model was used with the Transfer Learning technique where-in the entire model was frozen and just the last 2 fully-connected layers were retrained. The results from this model were adequate enough, as seen from Fig.2. , Fig.3. & Fig.4. , to be merged with the GUI and report generator.

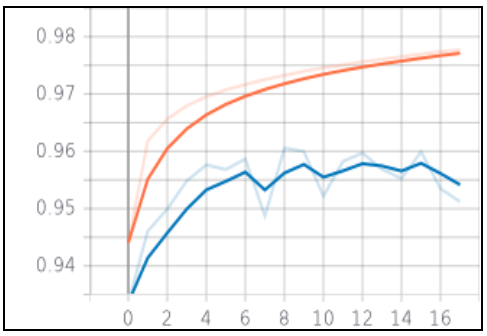


Fig -2: Model Specificity

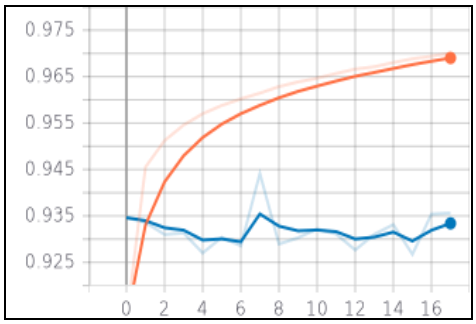


Fig -3: Model Recall

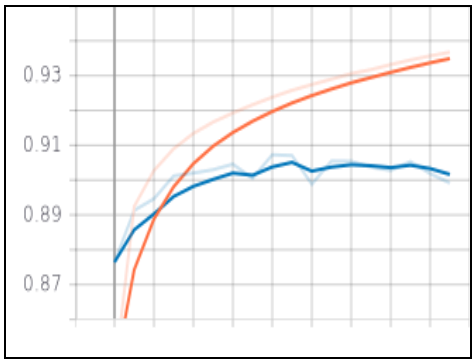


Fig -4: Model F1-Score

4. USER EXPERIENCE

4.1 Graphical user interface

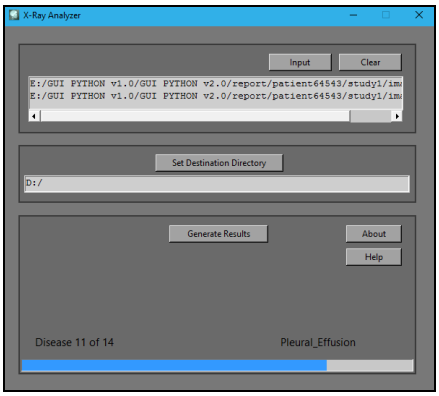


Fig -5: Graphical user interface

The GUI Fig.5. was designed using Tkinter a Python library, so that any user operating the system can use it to pass X-ray images of the patients to the model and obtain the results without any hassle or knowing the base code.

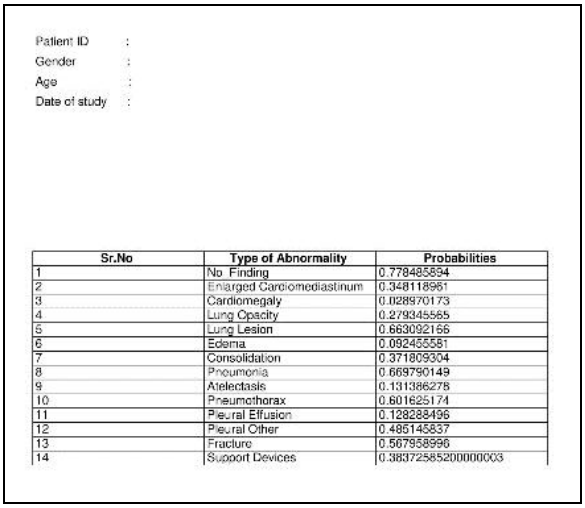
The user has to first select the X-ray image(s) by clicking on the Input button followed by which the paths of the selected images will be displayed in the List-box. Then the user has to select the destination path where he wants the results to be stored. On clicking the Generate Results button the selected X-ray image(s) are sent to the model and the images are evaluated for the abnormalities and the GUI displays the progress. Finally, once all the results are generated a report is created for each patient.

4.2 Patient report generation

The patient report is generated in a Portable Document Format (PDF) format which contains the details of the analysis of patient's chest X-ray image after passing through the model, as seen in Fig.6. & Fig.7.

The Python library used for the generation of this patient report is FPDF. The probabilities of the abnormalities found in the chest X-ray image by the model, are generated in an Excel file. By using the Python libraries like Pandas and FPDF, these values are fetched and put into a tabular form in the PDF file.

The X-ray image which was passed through the model is also appended to the PDF report file after the table. The Python script generates reports per patient based on the X-ray images selected.



Sr.No	Type of Abnormality	Probabilities
1	No Finding	0.778485894
2	Enlarged Cardiomediastinum	0.348118961
3	Cardiomegaly	0.028970173
4	Lung Opacity	0.279345565
5	Lung Lesion	0.663092166
6	Edema	0.092455581
7	Consolidation	0.371809304
8	Pneumonia	0.669790149
9	Atelectasis	0.131386278
10	Pneumothorax	0.601625174
11	Pleural Effusion	0.128288496
12	Pleural Other	0.486145837
13	Fracture	0.567958996
14	Support Devices	0.38372585200000003

Fig -6: Patient report page 1

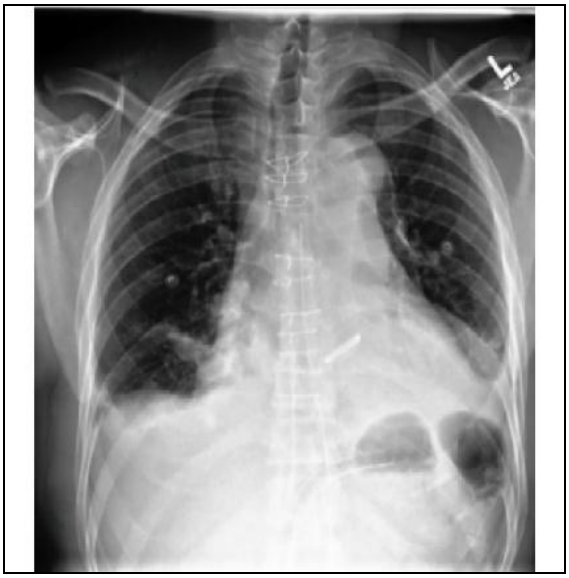


Fig -7: Patient report page 2

5. CONCLUSIONS

The goal of this project was to create a user friendly and reliable system for detecting chest abnormalities and streamlining workflow at radiology centres.

The performance of our system is adequate for deployment, but is limited due to legal constraints from the 2 datasets [1] & [2], which prevent the full-fledged deployment of this system.

This paper provides a proof of concept that such a system can be constructed using a well labelled, large dataset if required, by fulfilling necessary legal requirements.

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