

# X-Ray Image Classifier Using DenseNet

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**ABSTRACT:** One of the most common types of radiology tests for the treatment of thorax diseases is chest X-ray (CXR). Detecting anomaly in chest X-ray images by advanced technology, such as deep learning, is a pressing need to boost work efficiency and accuracy in diagnosis. The main objective of this work is to improve the efficiency of the task of diagnosis of thorax diseases by using DenseNet model for classification of X-ray images and to solve the problem of transformation methods in the task of classification of multi labels. The experimental study is being conducted on dataset ChestX-ray8. The results show that the proposed approach outperformed the current state of the art, and visualized using GradCAM for the model operation.

**KEYWORDS:** Convolutional Neural Network, Image Classification, Deeplearning, , DenseNet, Thoracic Pathologies, GradCAM, ROC, CXR

## I. INTRODUCTION

The thorax, which is sometimes called the chest, is the upper portion of the body between the neck and the abdomen. The rib cage, neck, and shoulder girdle are largely secured and supported. The rib cage is surrounded by neighbouring ribs and muscles and includes viscera, primarily the lungs, heart and mediastinum organs, which play a vital role in feeding (esophagus), breathing and blood circulation.

Medical image processing is an active field of machine learning science, partially because the data are fairly organized and named, and this is likely to be the environment where patients communicate with working, functional artificial intelligence systems first. Chest X-ray, colloquially referred to as Chest X-Ray(CXR), is one of the most common forms of radiology evaluation for thorax disease diagnosis. Under conditions of ambiguity, however, radiology requires decision-making, and thus cannot always provide infallible interpretations or studies. The project does not aim to substitute or compete with physicians but can be seen as a supplementary "second opinion" to a radiologist's.

Transfer learning using CNN is a widely used technique for addressing the task of classifying medical images, where a pre-trained CNN such as DenseNet is used on huge dataset. The methodology used here explores how to manage class disparity Test diagnostic output by calculating the ROC (Receiver Operating Characteristic) AUC (Area Under the Curve) curve and visualizing it using GradCAMs.

## II. RELATED WORK

Chest X-ray[1] is the most common means of detecting lung lesion and deep learning is a strong diagnostic aid. Due to limitations in data size, labelling and computer hardware, it is promising to fine-tune existing deep networks for classification tasks of chest X-ray images. However, it may lead to low transfer efficiency, overfitting and other problems when chest X-ray dataset and source dataset are totally different. [2]Training data or class disparity is also a major problem in medical image analysis. This data imbalance effect may be enhanced by using data increase to produce more training images of unusual or uncommon data, but there is a chance of overfitting. [3]A novel approach for applying CNN models to detect and identify TB manifestations in X-ray images is studied where CNN is used to detect TB in a large, unbalanced, lower-category dataset, and a range of optimization solutions is used to further improve accuracy. [4]A new approach is being studied which combines the effectiveness of CNN for image feature extraction and the power of supervised multi-label classifiers to address the task of detecting thorax diseases on CXRs. The function was performed with a pre-trained model of the DenseNet-121. Results showed the system obtained excellent results and outperformed the existing state-of-the-art data collection on ChestX-ray14. A variety of changes should be made to further substantiate the findings of this analysis, such as the use of an attention method to enhance the work of CNN and train our classifier on a more balanced dataset to avoid the issue of imbalance label distribution.

### III. METHODOLOGY

The steps for building and evaluating the deep learning classifier model is as follows:

**Step 1:** Pre-process and prepare the X-ray dataset

**Step 2:** Use transfer learning to retrain a DenseNet model for X-ray image classification

**Step 3:** Implement a technique to handle class imbalance

**Step 4:** Measure diagnostic performance by computing the AUC (Area Under the Curve) for the ROC (Receiver Operating Characteristic) curve

**Step 5:** Visualize model activity using GradCAMs

The proposed architecture of the model is as shown:

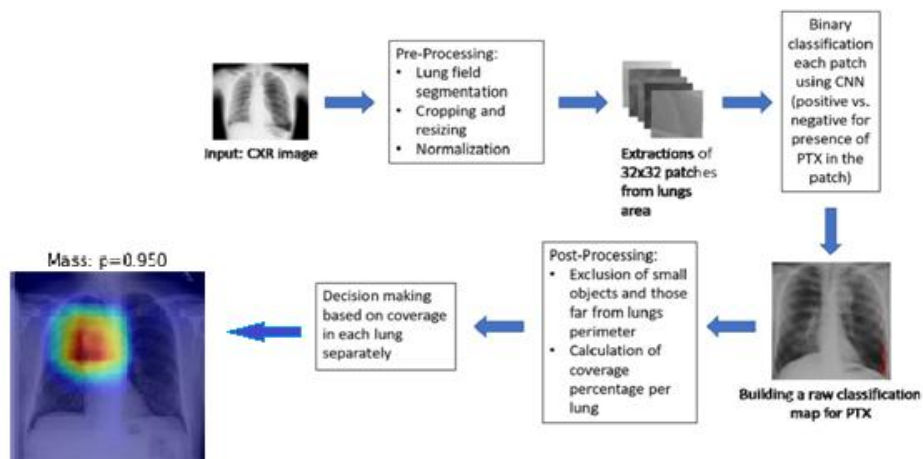


Fig 3. Proposed System

#### 3.1 Load the Datasets:

The first stage of the proposed model is image processing from the data sets. I.e. ChestX-ray8 that has 108,948 front-view X-ray images of 32,717 individual patients where each image in the data set includes several text-mined labels representing 14 different pathological conditions. These in turn can be used by physicians to diagnose 8 different diseases. We will use this data to create a single model that will provide binary classification predictions for each of the 14 named pathologies. In other words, for each of the pathologies it will predict 'positive' or 'negative.'

#### 3.2 Preventing data leakage:

It is worth remembering that we have several photos for each patient in our dataset. Of example, this may be the case when a patient has taken several X-ray images during their visits to hospital at various times. We also ensured in our data splitting that the separation is performed at the patient level so that there is no data "leakage" between the train, validation, and test datasets.

### 3.3 Preparing images:

The Keras ImageDataGenerator class is used which allows us to create a "generator" for images specified in a data frame. This class also offers support for simple data increase including random horizontal picture flipping. The scale of the image is set 320px by 320px.

### 3.4 Model Development:

#### 3.4.1 Class Imbalance:

However, there are few practical problems to overcome before a neural network is fully educated. The first is an inequality between groups. One of the difficulties of working with datasets for medical diagnosis is the broad class disparity present in these datasets.

As we see in fig(3.4.1.a) below, positive case contributions are substantially lower than negative contributions. We want to be equal in the contributions though. One way to do that is by multiplying each example from each class by a class-specific weight factor,  $w_{pos}$  and  $w_{neg}$ , such that each class's total contribution is equivalent.

To have this, we want,

$$w_{pos} \times freq_p = w_{neg} \times freq_n, w_{pos} \times freq_p = w_{neg} \times freq_n,$$

which we can do simply by taking,

$$w_{pos} = freq_n \times w_{neg} = freq_n$$

$$w_{neg} = freq_p \times w_{pos} = freq_p$$

This way, we will be balancing the contribution of positive and negative labels.

The fig(3.4.1.b) below shows, by applying these weightings the positive and negative labels within each class would have the same aggregate contribution to the loss function. Now let's implement such a loss function.

After computing the weights, our final weighted loss for each training case will be:

$$w_{cross-entropy}(x) = -(w_p y \log(f(x)) + w_n (1-y) \log(1-f(x))).$$

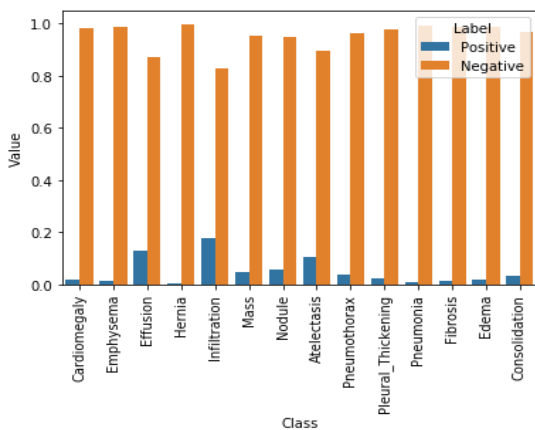


Fig 3.4.1.a Class Imbalance

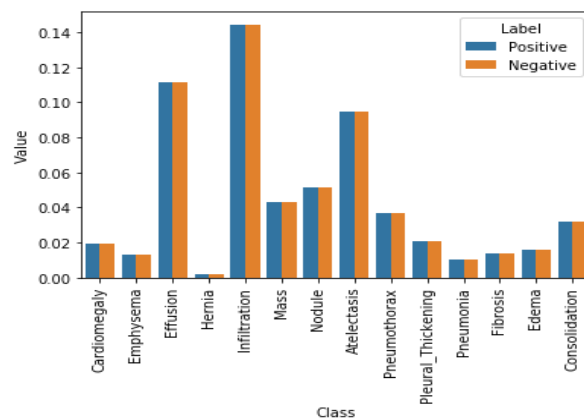


Fig 3.4.1.b Perfectly Balanced

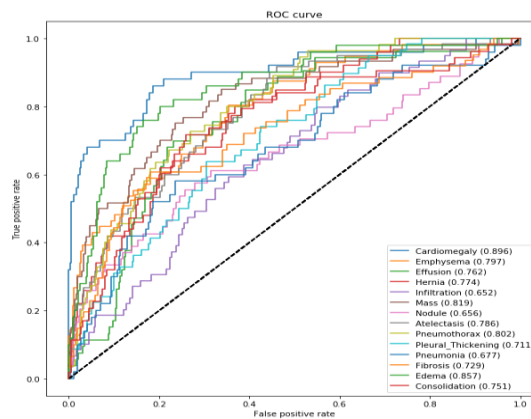
**3.4.2 DenseNet121 :**

We're going to use a pre-trained DenseNet121 model that we can load directly from Keras, and then add two layers:

1. A GlobalAveragePooling2D layer that gets DenseNet121 's average of the last convolution layers.
2. A Dense layer with sigmoid activation for each of our classes to get the predictive logits.

**3.5 ROC Curve and AUROC:**

The model is evaluated using ROC and AUC curve as shown in the below fig(3.5)



**Fig 3.5 ROC curve for model Evaluation**

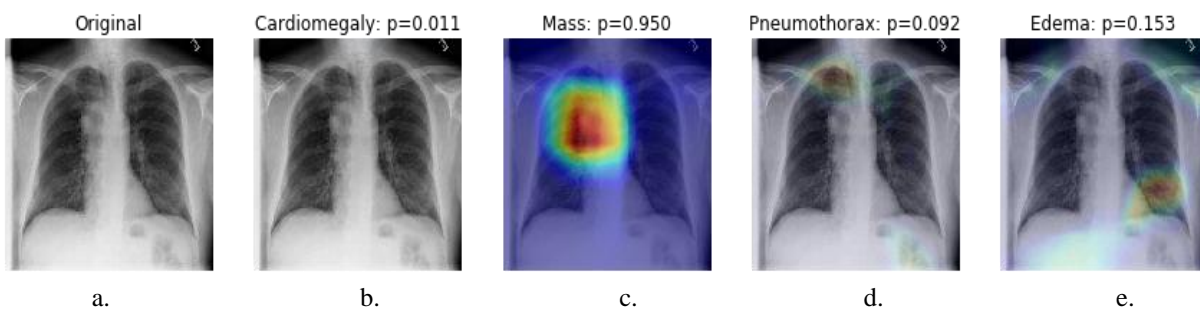
**3.6 Visualizing Learning with GradCAM:**

Some of the drawbacks of using profound medical learning is that the dynamic architecture used by neural networks makes it much harder to understand compared to standard models of machine learning ( e.g. linear models). The use of Class Activation Maps (CAM) is one of the most popular methods to improve the interpretability of models for computer vision tasks. Class activation maps are useful for understanding where the model is "looking" when classifying an image.

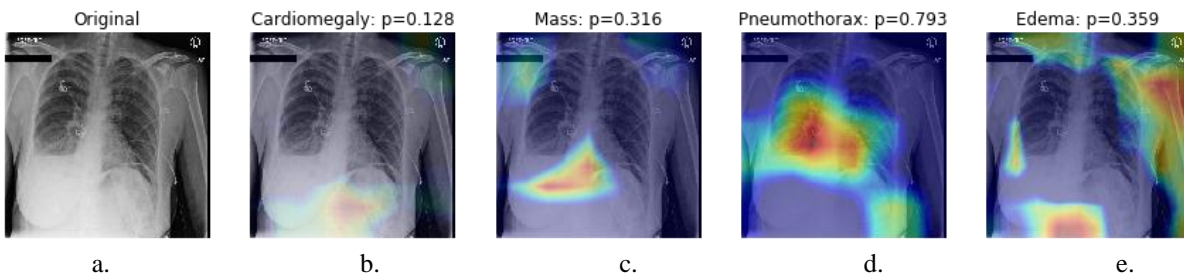
**IV. EXPERIMENTAL RESULTS**

The project is a python implementation. Jupyter Notebook executes the Python program. In this project, there are several stages implemented, such as pre-processing data, testing for data leakage, training a pre-trained model and evaluating the model using the AUC.

The following figures(fig 4.1 & 4.2) shows the results of X-Ray Image Classification and pathology detection.



**Fig 4.1: X-Ray Image Classification (a) Original image (b)Classification 1 (c) Classification 2( with correct pathology detection- MASS) (d) classification 3 (e) Classification 4**



**Fig 4.2: X-Ray Image Classification (a) Original image (b)Classification 1 (c) Classification 2 (d) classification 3 ( with correct pathology detection- Pneumothorax) (e) Classification 4**

The table-1 gives the detailed description about all the possible initial test cases which are required for the project:

Test case	Test case description	Input	Output	Test case result
1	Uploading image	Image dataset	Processing image frames	Pass
2	Addressing Class Imbalance	Processed image	Balanced positive and negative labels	Pass
3	Pathology Detection	frames	Classifying	Pass
4	Visualizing activity	frames	Activity visualized as, Edema ,Mass, Pneumothorax, etc	Pass

## V. CONCLUSION

A precise and efficient Chest X-Ray image classifier has been built in this paper which achieves comparable metrics with the current state-of-the-art system. This paper uses the latest machine learning and computer vision methods, deep learning and AI. The evaluation process was conducted using performance metrics such as ROC and AUC curves. The model's interpretability is done using Class Activation Maps. The results showed that our approach to the ChestX-ray8 dataset obtained substantial results and outperformed the present cutting edge technology. A variety of changes should be made to further substantiate the findings of this analysis, such as the use of an attention method to enhance the work of CNN and train our classifier on a more balanced dataset to avoid the issue of imbalance label distribution.

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