# Introduction

Soon after the discovery of x-rays in 1895, radiology i.e. use of x-ray technology for medical image analysis became very popular as it opened unseen doors in the world of human health treatment. Treatments of illnesses in chest region and bone damage detection became more accurate and precise. Then after the invention of computers and machine learning techniques whereby using statistical formulas and functions computers are taught to perform work like doing repetitive tasks, identification, prediction of required data etc. became prominent. Many machine learning researchers especially in the field of CNN have worked on developing a machine learning model which identifies any object presented to it. In this paper using similar principles of machine learning for classification of images we would be trying to get a highly precise model for identification of chest related diseases like pneumonia, covid-19 etc. (Wang, et al., n.d.) The advantage of using deep neural networks lies in the very word deep were in there are many layers through which the data passes and on each passing layer, we identify the features of that data and make a note of it via updating our weights and biases accordingly. To have a better performance at every stage we can train it with large-scale datasets which are unique in some ways which will also help to avoid overfitting.

(Krizhevsky, et al., 2012)

In this paper, we will make use of basic exploratory data analytics i.e. data visualization and pre-processing which involves cleaning up the data and plotting charts and graphs to get a gist of data we would be using on our machine learning models, later on we will divide that dataset into train and test sets and pass the former over our machine learning models to train them and then valid their performances by checking their output on test set, this process can be repeated N number of times depending upon our satisfaction as we increase this process of train and test, the model’s performance also known as accuracy measure tends to improve overtime. One thing to keep in mind is that no matter the number of loops or epochs as known in the machine learning world, we can’t keep it running forever as at certain point it reaches a stage where it gets overfitted for our training data so we need to try permutations and combinations from the dataset to have a diverse train and test cases and also make sure that the model we are trying to train has the required layers which works very well on our dataset when it comes to extraction of features and processing or adjusting the weights in those layers accordingly. Also, we will be using Gradient-weighted Class Activation Mapping (Grad-CAM) which will highlight the region of interest which are identified by our trained model to classify the input image.

A picture containing film, sitting, laying, person

Description automatically generatedBackground pattern

Description automatically generated

Figure 1: Regular Covid X-Ray, Covid X-ray Image with Grad-CAM

# Literature Review

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| --- | --- | --- | --- | --- | --- |
| Author(s) | Research Question/Purpose | Title | Search Terms | Data Synthesis | Finding |
| Gianluca Maguoloa, Loris Nannia | To prove that several testing protocols for recognition are always right for neural network to identify covid19 | A Critic Evaluation of Methods for COVID-19 Automatic Detection from X-Ray Images  (2020) | Covid-19; Covid-19 Diagnosis; Convolutional Neural Networks; X- Ray Images | 108,948 images of 32,717 different patients, classified into 8 different sectors |  |
| T. Rahman, M. E. H. Chowdhury, A. Khandakar, Khandaker R. I., Khandaker F. Islam, Z. B. Mahbub, M. A. Kadir and S. Kashem | Report on advances in accurate detection of pneumonia using transfer learning methods | Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X-ray.  (2020) | pneumonia; bacterial and viral pneumonia; chest X-ray; deep learning; transfer learning; image processing | 5247 chest X-ray images consisting of bacterial, viral, and normal chest x-rays images were pre-processed and trained for the transfer learning-based classification | Authors used 4 models out of which DenseNet201 outperformed rest of the models in classification. |
| R. Selvaraju, M. Cogswell, Abhishek Das, R. Vedantam, D. Parikh, D. Batra | Proposed a Novel way to make any CNN-based model more transparent in visual explanation | Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization  (2019) | CNN,  VGG16,  ResNet |  | Results show that the authors were able to achieve what they intended to do. |
| Ivo M. Baltruschat, Hannes Nickisch, Michael Grass, Tobias Knopp, and Axel Saalbach | Building a model using transfer learning and testing with and without fine tuning it. | Comparison of Deep Learning Approaches for Multi-Label Chest X-Ray Classification  (2019) | X-Ray, Deep Learning, Convolutional Neural Networks | ChestX-ray14 consists of 112,120 frontal chest X-rays from 30,805 patients |  |
| X. Wang, Y. Peng, Le Lu, Z. Lu, M. Bagheri, Ronald M. Summers | To demonstrate that thoracic diseases can be detected and even spatially-located via a unified weakly-supervised multi-label image classification and disease localization framework | ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common Thorax Diseases  (2017) |  | 108,948 frontal view X-ray images of 32,717 unique patients with the text mined eight disease image labels | Authors conducted quantitative performance on the ChestX-ray8 db using transfer learning techniques. |
| Mohammad Tariqul Islam, Md Abdul Aowal, Ahmed Tahseen Minhaz, Khalid Ashraf | DCNN based classification and localization on the publicly available datasets | Abnormality Detection and Localization in Chest X-Rays using Deep Convolutional Neural Networks(2017) | Abnormality detection | 7284 CXRs, both frontal and lateral images. Another one with 247 chest X-rays, among which 154 have lung nodules and 93 have no nodules. | The DCNN architecture they used didn’t perform well on all abnormalities. |
| P. Rajpurkar, J. Irvin, K. Zhu, B. Yang , H. Mehta, T. Duan, D. Ding, A. Bagul, Robyn L. Ball, Curtis L. , Kate Sh., M. Lungren, Andrew Y. Ng, | Develop an Algorithm which can detect pneumonia from chest x-ray. | CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning  (2017) | CheXNet | Chest Xray dataset of 100,000 frontal view X-ray images with 14 diseases. | Authors created a 121 Dense Convolutional Network called CheXNet which was able to perform better than radiologist given the data under certain circumstances. |
| Juan Manuel Carrillo-de-Gea, Ginés García-Mateos, José Luis Fernández-Alemán and José Luis Hernández-Hernández | Objective of the paper is to perform an automatic normality classification of posteroanterior chest radiographs. | A Computer-Aided Detection System for Digital Chest Radiographs  (2016) | Medical Imaging | DICOM images of chest radiographs (23 women and 25 men) were provided by HGURSM, Spain to perform the test. | A new approach for detection of normality in chest radiographies was given which is based on LBP. |
| Kaiming He,Xiangyu Zhang, Shaoqing Ren, Jian Sun |  | Deep Residual Learning for Image Recognition  (2015) | Deep neural network, ILSVRC 2015,  Residual Learning,  COCO object detection. | ImageNet dataset,  CIFAR-10 |  |
| Saad, Mohd Nizam; Muda, Zurina; Sahari, Noraidh; Hamid, Hamzaini Abdul | Segmentation of Lungs based on object detection technqiues. | Image Segmentation for Lung region in Chest Xray Images using Edge Detection and Morphology(2014) | Lungs, Image edge detection, shape, noise, biomedical imaging. | 247 CXR images with  standard size of 2048 x 2048 pixel | Researcher did built a method for lung segmentation however there are some changes and improvements needed as pointed out by the authors themselves. |
| Alex Krizhevsky,  Ilya Sutskever,  Geoffrey E. Hinton | Create a Model which works efficiently over huge datasets | ImageNet Classification with Deep Convolutional Neural Networks  (2012) |  | 1.2 million high-resolution images were trained for ImageNet LSVRC-2010 contest into the 1000 classes | Large networks tend to achieve good results on huge datasets with supervised learning. Authors want to try the same on video sequence. |

**INTRODUCTION**

To begin with as we know that the use of deep neural network technique called convolutional neural networks (CNN hereafter) in medical image diagnosis is not a new phenomenon also a lot of work has been done in the world of computer vision which has helped us develop models which can be able to classify various objects properly. In this section we would be discussing some work of previous researchers and how we can understand, learn and fill-in the gaps of their work and help reach the common objective of uplifting medical image diagnosis.

Use of Transfer Learning Methodologies in Chest X-ray classification

As per (Tawsifur Rahman, 2020)’s research, one of the greatest causes for child fatalities around the world is pneumonia because of which more than 1 million children die among which 18% of the total deaths is of children less than 5 years of age at the same time globally around 2 billion people suffered from pneumonia. They also found that chest x rays among others is the best method to detect pneumonia even though it’s not very clear and sometimes leads to misclassification to other diseases. In their paper there objective is to provide a CNN-based transfer learning approach using 4 pre-trained models which were ResNet18, DenseNet201, SqueezeNet and AlexNet to detect and classify two forms of known pneumonia which are bacterial and viral. They worked on a dataset which comprised of mixed cases of pneumonia i.e. viral and bacterial infected along with normal pictures of around 5247 chest x-ray images, it didn’t have any cases where both viral and bacterial infection was found in one patient. They also made use of data augmentation so as to increase the number of datapoints and improve the quality of the dataset as it’s a better and inexpensive alternative to collecting new data. Since they were focusing on a very niche disease i.e. pneumonia, they were able to get a pretty decent accuracy for their models DenseNet201 leading the way.

Recent work on Covid-19 data

Covid-19 the pandemic which has stopped the wheel of the world on all fronts also has some window of opportunities for research. To address this (Maguolo & Nannia, 2020) compared different methods and testing protocols used to automatically diagnose covid-19 from x-ray pictures and they were able to showcase that identical outcomes can be achieved using those pictures which did not had most part of the lungs. They made use of four different datasets available publicly online. They also performed a unique approach wherein they first covered the images with a black box in the centre which covered most of the lung region and then it was sent to AlexNet for classification based on labelled set to those images before they were transformed with black box in front. The model was trained to recognize the source of the dataset which in turn tried to prove that models are biased as they learn to classify more on the source dataset rather than on correct medical diagnosis. This was a very novel way of approaching not just covid-19 diagnosis but any serious medical image classifying problem in general.

AlexNet

Geffrey Hilton is regarded as one of the most pioneering figure in the area of research related to deep neural networks, in his paper along with his colleagues they developed a deep convolutional model named AlexNet (Kaiming He, 2015) which was able to classify more than 1 million high- resolution pictures in a contest to differentiate up to 1000 different classes. They did this by training almost 600,000+ neurons which consisted of 5 convolutional layers. For training their model they made use of a sub-set of ImageNet dataset which around 1.2 million training pictures and roughly 50,000 to 150,000 for validation and testing. Considering the size of dataset and length of network, they spread out the network across two GTX 580 GPUs each of 3GB in memory using parallelism. Since their network architecture was dense, they had to face an issue of overfitting and to combat that they made use of two techniques namely Data Augmentation and Dropout. Advantage of using data augmentation is that the transformed images which they’ve generated using the existing ones don’t need to be stored on the disk instead they’re generated via code on CPU while the GPU trains on the preceding array of pictures. Also, in the technique called Dropout, every neuron in the hidden layer with a probability of 0.5 was set to zero in this way they didn’t contribute to the backpropagation. In this way they achieved good output on an immensely challenging dataset using just supervised learning (Krizhevsky, et al., 2012).

Some previous work on pneumonia detection using chest x-ray images

As per (Rajpurkar, et al., 2017)’s study, more than a million people are affected with pneumonia every year in the United States alone out of which nearly 50,000 people die due to this disease. To tackle this issue they built a 121-layer dense convolutional network model called CheXNet which has dense connections and batch normalization for optimization of deep network tractable, which they claim can detect pneumonia in par with radiologists and in some cases even exceed their predictions also it outperformed all other best known published results for 14 different pathologies in the dataset called ChestX-ray14. Although while validating their claims there were some limitations which are worth considering, firstly they made use of only frontal radiographs to test their model and same was given to radiologists also the radiologists involved in this project and the model were not given permission to use current or past patient information in any way or manner which impacts the performance of radiologists in general. Overall the model generated performed quite well and the results obtained showed a way to the machine learning community that medical imaging technology can be automated to improve the healthcare delivery where access to radiologists is not possible.

Image Segmentation

Image Segmentation has always been an interesting area of research which distinguishes objects area from one and another in pictures, early edge detection methods like Laplacian, Prewitt and Sobel were used but the problem with that was that it failed in cases where they acted as high pass filter and were affected by noise present in the picture, to overcome this issue (Saad, et al., 2014) proposed a better algorithm which is good at edge detection and can cope up with lower and upper threshold units for image noise and combined it with morphology methods for fined outputs. In order to address this issue, they made use of Euler number method.

Multi-Label Chest X-Ray Classification

As per (Baltruschat, et al., 2018) over 23,000 chest x-ray images didn’t went through certified radiologist at Queen Alexandra Medical Institution alone and a handful of patients suffered because their x-ray images weren’t being properly accessed. This is not just the only medical institution which has these kind of issues as aging population is growing due to increase in life expectancy, the requirement for healthcare workers and clinicians has also driven up. This observation made them to build a computer vision model which makes use of transfer learning and classifies images based on the features learned by their model. The model they created is loosed based on ResNet-50, they fined tuned some layers of that model to suit their needs at the same time they made use of Grad-CAM which helped them get insights their model. The dataset they used was of 14 different chest related diseases which we’ve also seen in other researches cited above. There optimized model ResNet-38 achieved better results in 5 out of 14 classes compared to the works they’ve cited also they observed substantial variability when different splits of the same dataset were considered.

Class Visualization

[Some paper] devise a method to identify neurons which were important through the Grad-CAM technique as even though computer vision models enable us to classify things, detect objects and do semantic segmentations, it’s still hard to interpret individual components. In order to get a reliable model we need to know how and why the model came to the predicted conclusion. This interpretability is not just useful when it comes to understand the conclusion part of the model but also while training it as it can help us make the training process smoother by helping us debug and fine tune the model efficiently, diagnosing classification models for considerable biased errors. As shown in the example given that the model to classify doctors and nurses was trained on a dataset which had 78% images of doctors who were men and 93% images of nurses who were women so the model instead of checking for props like stethoscope went for features like facial dimensions, hair length etc and classified all women as nurses while all men as doctors. This issue was identified using grad-cam technique which highlights the region of interest based on which the model made it’s classification. Further the model was retrained with more images this time balancing it out with more female doctors and more male nurses to lower the bias results. This helped to demonstrate that grad-cam technique can help not just visualize the output of the trained model but also fix issues if any.

Detection of Abnormality in Digital Chest Radiography with the aid of Computer Detection Systems

[Some paper] proposed a method to perform automatic normality classification of posteroanterior digital chest radiographs which is able to detect anything which can be classified as different from normality. Initially images of 3000 by 3000 pixels with depth of 12 bits per pixel were taken with an average age of 55. These images were reduced in pixel depth by 4 bits i.e. from 12 to 8 after which decimation is applied to the image using supersampling interpolation which reduced the size by 2000 i.e. to 1000 x 1000 which is considered the standard resolution for further steps.

In the next step of segmentation, image is segmented to locate the position of both lungs which then helps them to determine the region of interest. Samples of both left and right lungs were extracted and the location with maximum correlation is selected as the expected position of each lung after which a grid of 3 by 4 region is generated. For feature extraction, they made use of LBP histogram for each reach obtained, later these features were classified based on distances between histograms i.e. using Bhattacharyya distance two histograms are computed. Later on the experimental results obtained from the classification were 90% for the best classifier speaking about the disadvantage, the method implied by the researchers relies mainly on texture information which in case of some diseases which affect only the intensity of the images would be hard to detect.

Detection of Abnormality and it’s Localization using DNN in Chest X-ray region.

[Some paper] made use of ensemble models to improve the classification accuracy for abnormality detection in chest region for x rays compared to a single model. They made use of some open datasets like JSRT dataset which contained around 250 images of which 154 had lung nodules i.e. malignant and benign cases and 93 didn’t have any nodules each of size 2048 x 2048 pixels and a gray-scale color depth of 12 bits, Shenzhen Dataset from China which had two classes i.e. normal and tuberculosis and Indiana chest X-ray dataset the largest amongst the 3 with 7284 chest x-ray images of both frontal and lateral with diseases like cardiomegaly, pulmonary and pleural effusion on which the first studied performances of some already built deep convolutional network over different abnormalities. For their experiment, they trained many models via transfer learning like AlexNet, VGG based and ResNet and for each they found some model performing better than other on certain diseases while some giving high sensitivity and specificity etc. For the ensemble of models, they trained the variants of the same mentioned model and used a simple linear averaging of probability on individual model as bagging and boosting are implied it might result in a biased model as the number of dataset is low for such huge model with multiple layers. They also tried to increase the number of models in the ensemble and found that gradually a consistent performance was seen after 9 models. For better understanding, like other researchers listed above they too went to visual depiction of model prediction to actually understand how and why the models were making the classification they were giving rather than just blindly treating it as a black box. Speaking in simple words they wanted to identify the features which contributed more to the output of the model. They took the localization approach for cardiomegaly abnormality and highlighted the 20% area which was more sensitive to the region where the heart is larger than normal heart. They performed the same experiment on around 50 samples of cardiomegaly and normal images and found the result to be mostly consistent. Based on the localization observation approach seeing sensitive region they came to a conclusion that characteristic features in the shape of heart and its surrounding regions is alone to detect cardiomegaly, the lungs are less important when it comes to detecting it. However while applying similar methods on pointed features for that of nature like bone fracture and lung nodule, the localization method failed.

Conclusion

After going through the literature mentioned above, it was seen that ample of research has been carried out in the area of image detection, medical image analysis etc even though some researchers in the domain of chest x- ray analysis and classification claim to have developed a model which performed better than a human radiologist, it’s interesting to note that the model built was only trained with frontal chest x-ray images also the human radiologists were not given any supporting data such as patient age, gender and previous health condition which still leaves a room for improvement and as a researcher myself it makes me curious to know what could have been the results if those kind of data would have been provided.

In the upcoming sections we would be seeing the proposed research methodology for our selected approach of building a model via transfer and ensemble learning.