Chest X-Ray Analysis For Classification of Various Diseases

Amita Yadav
Dept of Computer Science and Engineering
Maharaja Surajmal Institute of Technology New Delhi, India.

Abstract- *Chest x-rays (CXR) are a frequently performed radiological investigation. The sheer volume of chest x-rays requested, however, is too large that they are often not reported immediately. In order to help interpret them in a more streamlined fashion, we propose a system to analyse the scan before it is subjugated to the radiologist's attention, thus saving time and resources in the process. Studying a chest x-ray scan is one of the most routine practices in a medical profession. Therefore before hitting the wards as doctors, it is essential that they develop the ability to interpret chest x-rays, of particular importance, is the ability to recognise findings that require immediate medical attention. This project aims at providing doctors the analysis before hand for them to corroborate and move on with the diagnosis. Our work contributes to the procedure by classification and localisation of the disease in the input image of the chest x-ray scan. The problem is a multi-class classification problem, in which the diseases are our target classes and their respective presence is what needs to be checked. Two methods that we plan to use for completing our research are training an entire network and then run the classifiers, and using the concept of transfer learning. We plan on using the trained network layers as the feature extraction layer in our model*

Keywords- AI, CXR, CAD, CNN

I. INTRODUCTION

Chest x-ray uses a very small dose of ionizing radiation to produce pictures of the inside of the chest. It is used to evaluate the lungs, heart and chest wall and may be used to help diagnose shortness of breath, persistent cough, fever, chest pain or injury. It also may be used to help diagnose and monitor treatment for a variety of lung conditions such as pneumonia, emphysema, and cancer. Because chest x-ray is fast and easy, it is particularly useful in emergency diagnosis and treatment. This exam requires little to no special preparation. The chest x-ray is the most commonly performed diagnostic x-ray examination. A chest x-ray produces images of the heart, lungs, airways, blood vessels and the bones of the spine and chest. An x-ray (radiograph) is a noninvasive medical test that helps physicians diagnose and treat medical conditions. Imaging with x-rays involves exposing a part of the body to a small dose of X-rays are a form of radiation like light or radio waves. X-rays pass through most objects, including the body. Once it is carefully aimed at the part of the body being examined, an x-ray machine produces a small burst of radiation that passes through the body, recording an image on photographic film or a special detector. Different parts of the body absorb the x-rays in varying degrees. Dense bone absorbs much of the radiation while soft tissue, such as muscle, fat, and organs, allow more of the x-rays to pass through them. As a result, bones appear white on the x-ray, soft tissue shows up in shades of gray and air appears black. On a chest x-ray, the ribs and spine will absorb much of the radiation and appear white or light gray on the image. Lung tissue absorbs little radiation and will appear dark on the image. Until recently, x-ray images were maintained on large film sheets (much like a large photographic negative). Today, most images are digital files that are stored electronically. These stored images are easily accessible for diagnosis and disease management.

A *radiologist*, a physician specifically trained to supervise and interpret radiology examinations, will analyze the images and send a signed report to your primary care or referring physician, who will discuss the *results* with you. The results of a chest x-ray can be available almost immediately for review by your physician. Follow-up examinations may be necessary. Your doctor will explain the exact reason why another exam is requested. Sometimes a follow-up exam is done because a potential abnormality needs further evaluation with additional views or a special imaging technique. A follow-up examination may also be necessary so that any change in a known abnormality can be monitored over time.Follow-up examinations are sometimes the best way to see if treatment is working or if a finding is stable or changed over time.

II. LITERATURESURVEY

Chest x-rays are the most commonly ordered diagnostic imaging tests, with millions of x-rays performed globally every year [1]. While the chest x-ray is frequently performed, interpreting a chest x-ray is one of the most subjective and complex of radiology tasks, with inter-reader agreement varying, depending on the level of experience of the reader, the abnormality being detected and the clinical setting [2]. Due to their wide availability and affordability, chest x-rays are performed all over the world, including remote areas with few or no radiologists. In some parts of the world, digital chest x-ray machines are more widely available than personnel sufficiently trained to report the x-rays they generated [3]. If automated detection can be applied in low-resource settings as a disease screening tool, the benefits to population health outcomes globally could be significant.

The Computer Aided Design (CAD) systems are mainly divided into the following steps: image preprocessing, extracting ROI regions, extracting ROI features, and classifying disease according to the features. The recent development of artificial intelligence (AI) combined with the accumulation of large volumes of medical images opens up new opportunities for building CAD systems in medical applications. Artificial intelligence methods, especially deep learning, mainly replace the process of feature extraction and disease classification in the traditional CAD systems. Artificial intelligence methods have also been widely used in image segmentation and bone suppression of chest X-ray. For the complex chest X-ray images, it takes a long time for researchers to find a good set of features that will be helpful of the CAD performance. Recently, due to the extensive and successful application of deep learning in different image recognition tasks (such as image classification [4] and semantic segmentation [5]), interest has been stimulated inreapplying deep learning to medical images. In particular, advances in deep learning and large database construction have made the algorithm “go beyond” the performance of medical professionals in a variety of medical imaging tasks, including pneumonia diagnosis [6], diabetic retinopathy detection [7] and bleeding identification[8]. Therefore, deep learning methods (especially CNN), which automatically learn image features to classify chest diseases, have become a mainstream trend.

Over the last few years, there has been increasing interest in the use of deep learning algorithms to assist with abnormality detection on medical images. This is a natural consequence of the rapidly growing ability of machines to interpret natural images and detect objects in them. On chest x-rays in particular, there have been a series of studies describing the use of deep learning algorithms to detect various abnormalities [8]. Most of these have been limited by the lack of availability of large, high-quality datasets a relatively small number considering that the majority of chest x-rays are normal, abnormal x-rays are less common and specific abnormalities being rarer still. The previously published work on deep learning for chest x-ray abnormality detection has not made a distinction between the diagnosis of ‘diseases’ and the detection of ‘abnormal findings’.

III. DATASETDESCRIPTION

The NIH Clinical Center recently released over 100,000 anonymized chest x-ray images and their corresponding data to the scientific community. NIH compiled the dataset of scans from more than 30,000 patients, including many with advanced lung disease. The images are classified mainly across 14 unique categories of diseases namely Atelectasis, Cardiomegaly, Effusion, Infiltration, Mass, Nodule, Pneumonia, Pneumothorax, Consolidation, Edema, Emphysema, Fibrosis, Pleural Thickening, Hernia.

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Total Dataset :1,20,000 images
Total Classes: 14
Image size : 1024x1024 pixels (RGB)
We chose three classes namely **Infiltration, Mass, Nodule, Pneumonia** each having 15000 images.

IV. METHODOLOGY

We plan to explore two different methodologies for this task, each method has its own tradeoff between the resources and accuracy. Training a model from scratch can lead to greater computational cost, memory but high accuracy whereas transfer learning has low computational and memory cost but can lead to lesser accuracy.

As we will see from the results, the effect of these tradeoffs are exhibited in the respective training models. We evaluated them using standard metrics and to evaluate their performance, as well as computational needs, we used a script to study the effect of training on the memory.

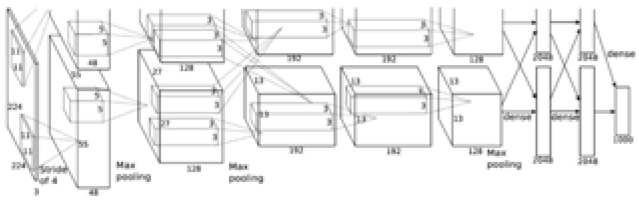

Fig 1. AlexNet

Training from scratch:

A Deep CNN model is trained on the data from scratch which is further optimized for accuracy after fine-tuning it. We will be training on AlexNet architecture shown in Fig. 1. The model consists of five convolution layers and 3 fully connected layers along with max-pooling and dropout layer, which attributes to 60 million parameters and 650, 000 neurons.

Training using Transfer Learning:

Transfer learning is a research problem in Machine learningthat focuses on storing knowledge gained while solving one problemand applyingittoadifferentbutrelatedproblem.Thebasicworkflow framework of transfer learning is depicted in Fig. 2.

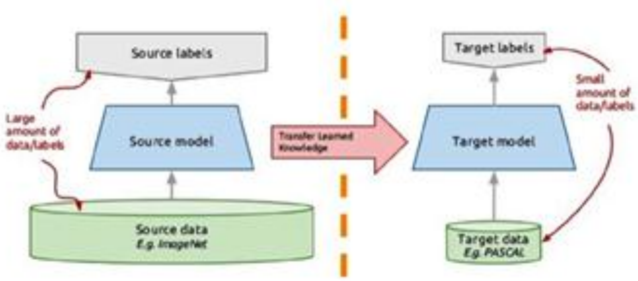

Fig 2. Transfer Learning

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V. TOOLS ANDFRAMEWORK

The different tools and framework that were used during different stages of the project were :

DataSetCollection : Scrapy Framework
Data Preprocessing : Numpy andPandas.
Deep Learning : PyTorch
Results and Evaluation : Matplotlib

All of the above mentioned tools are either libraries or entire frameworks implemented in the programming language Python.

VI. EXPERIMENTS ANDRESULTS

We carry out two set of experiments on training from scratch and transfer learning.

Implementation of scratch training

AlexNet

AlexNet was proposed in [16] with five convolutional and three fully-connected layers. With 60 million parameters, the network was trained using a subset of about 1.2 million images from the ImageNet dataset for classifying about 150,000 images into 1000 different categories. The success of AlexNet on a large-scale image classification problem led to several works that used pre-trained networks for feature representations which are fed to an application specific classifier. We follow a similar approach for recognition of individuals in patterned species, with a modification of the input size and consequently the feature map dimensions.

Table 1. The accuracy results obtained from **Scratch Training**

Accuracy	65.1%
Nodule	67.4%
Mass	56.7%
Pneumonia	68.5%

Implementation of transfer learning

We use a VggNet(Fig. 8) for the purpose of transfer learning. A VggNetpretrained on the ImageNet dataset is used as the feature extractor which is further fed to a smaller two fully connected neural network for the purpose of classification.

VggNet Architecture

The VGG network architecture was introduced by Simonyan and Zisserman in their 2014 paper, Very Deep Convolutional Networks for Large Scale Image Recognition. This network is characterized by its simplicity, using only 3×3 convolutional layers stacked on top of each other in increasing depth. Reducing volume size is handled by max pooling. Two fully-connected layers, each with 4,096 nodes are then followed by a softmax classifier. The "16" and "19" stand for the number of weight layers in the network.

In 2014, 16 and 19 layer networks were considered very deep (although we now have the ResNet architecture which can be successfully trained at depths of 50-200 for ImageNet and over 1,000 for CIFAR-10). Simonyan and Zisserman found training VGG16 and VGG19 challenging (specifically regarding convergence on the deeper networks), so in order to make training easier, they first trained smaller versions of VGG with less weight layers (columns A and C) first.

Table 2. The accuracy results obtained from **Transfer Learning**

Accuracy	**72.7%**
Nodule	**75.7%**
Mass	**68.9%**
Pneumonia	**73.1%**

A learning rule is an algorithm for updating the weights of a network in order to achieve a particular goal. One particular common goal is to minimize a error function associated with the network, also referred to as an objective or cost function.

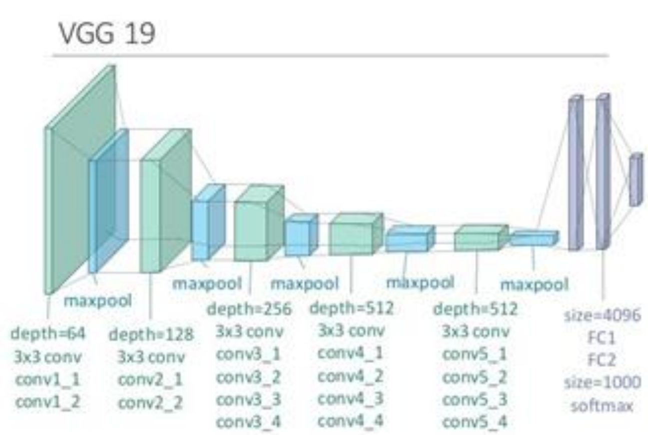

Fig. 3 VGG Network Architecture

VII. FUTUREWORK

We plan to extend current setting to real time applications by investigating various smaller architectures tiny-yolo,U-net and other deep model compression technique. We aim to implement them using frameworks like tensorflow-lite which will give it the capability to run on smaller devices like mobile phones in real time. Since the current framework with VggNet is giving promising results we will be exploring other frameworks which have been introduced in the literature recently for the same like Capsule Net.

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