Pneumonia Detection in Chest X-Ray Images by using Resnet-50

Ms. Malar M
PG Scholar-ECE
Kalaignar karunanidhi Institute of Technology
Coimbatore, Tamil Nadu

Mr. S. Maria Antony
Assistant Professor (SI.G)
Kalaignar karunanidhi Institute of Technology
Coimbatore, Tamil Nadu

Dr.Parimala Gandhi Ayyavu
Associate Professor-ECE
Kalaignar karunanidhi Institute of Technology
Coimbatore, Tamil Nadu

Abstract— Pneumonia is an infection that inflames the airsacs in one or both lungs.Pneumonia which is a dangerous disease that may occur in one or both lungs, usually caused by viruses, fungi, or bacteria. Due to Pneumonia's resemblance to other lung diseases, diagnosing and treating it from chest X-ray pictures can be challenging. A significant level of accuracy cannot be achieved by the current approaches for forecasting Pneumonia. In order to make the diagnosis of Pneumonia on X-ray pictures simple, we are using residual networks. RESNET50 model, which has been pre-trained on the ImageNet database. In addition, features learned by pre-trained RNN models on large-scale datasets are very useful in image classification tasks. By extracting the features of X-ray images, we can detect the Pneumonia.

Keywords—Pneumonia, ResNet50, Convolutional Neural Networks, Feature Extraction, Deep learning.

I. INTRODUCTION

Pneumonia is the single largest infectious cause of death in children worldwide. Pneumonia killed 740 180 children under the age of 5 in 2019, accounting for 14% of all deaths of children under 5 years old but 22% of all deaths in children aged one to five years [1]. In the US, the annual incidence is 24.8 cases per 10,000 adults, with higher rates as age increases. Pneumonia is the eighth leading cause of death and first among infectious causes of death. The mortality rate is as high as 23% for patients admitted to the intensive care unit for severe pneumonia [2].

Pneumonia is inflammation and fluid in your lungs caused by a bacterial, viral, or fungal infection [3]. It makes it difficult to breathe and can cause a fever and cough with yellow, green or bloody mucus. The flu, COVID-19, and pneumococcal disease are common causes of pneumonia [4]. The doctors suggest some tests to confirm the diagnosis of Pneumonia. Blood test to confirm the infection and to try to identify the germ. Pulse oximetry to measure the oxygen level in blood. Sputum rests on a sample of mucus taken after a deep coughto look for the source of the infection [5].

For the high-risk patients, the doctors may want to do some additional tests, including aCT scan, Arterial blood gas test, Pleural fluid culture, andBronchoscopy [6]. Currently, chest X-rays are one of the best methods for the detection of Pneumonia [7].

X-ray imaging over CT imaging because CT imaging typically takes considerably more time than X-ray imaging sufficienthigh-quality CT scanners may not be available in many underdeveloped regions. In contrast, X-rays are the most common and widely available diagnostic imaging technique, playing a crucial role in clinical care and epidemiological studies [8,9].

Computer-aided diagnosing using artificial-intelligence based solutions is becoming increasingly popular these days [10]. This facility can be made available to a large population at a minimal cost. Deep learning techniques solve all these problems, and their accuracy in the prediction of the disease is the same and sometimes even greater than an average radiologist [11]. Among the deep learning techniques, convolutional neural networks (CNNs) have shown great promise in mage classification and

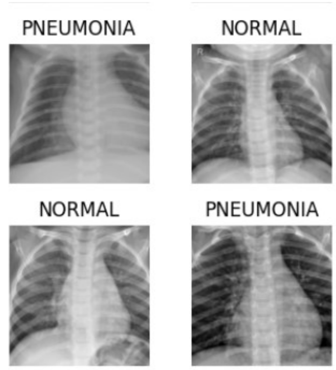

Fig 1, An example of a normal chest X-ray and pneumonia chest

X-ray images from the dataset. The Keras Image data generator is used to perform the data augmentation, where we aim to gain the overall increment in the generalization of the model [14].The model is pre-trained in ResNet using the dataset. Then, the model is used to predict pneumonia by using chest X-ray images [15].

The structure of this paper is described as follows: Section 2, provides s a description of the related research done in the same field. In Section 3, there is a description of all the details relevant to the dataset used. In Section 4, a description of the applied methodology has been provided, which has been divided into multiple stages. In Section 5, we present the experimental setup for the experiments carried out on different variants of the pre-trained ResNet model. Section 6 consists of results and discussions.

II. RELATED WORK

In recent times, the exploration of Machine learning (ML) algorithms in detecting thoracic diseases has gained attention in the research area of medical image classification. Lakhani and Sundaram (2017) [13] proposed a method of detecting pulmonary tuberculosis following the architecture of two different DCNNs, AlexNet and GoogleNet. Lung nodule classification, mainly for diagnosing lung cancer, proposed by Huang et al. [14] also adopted deep learning techniques. The performance of different variants of Convolutional Neural Networks (CNNs) for abnormality detection in chest X-Rays were proposed by Islam et al. [15] using the publicly available OpenI dataset [16]. For a better exploration of machine learning in chest screening, Wang et al. (2017) released a larger dataset of frontal chest X-Rays. Recently, Pranav Rajpurkar, Jeremy Irvin, et al. (2017) [17] explored this dataset for detecting pneumonia at a level better than radiologists. They referred to their model as ChexNet, which uses DenseNet-121 layer architecture for detecting all the 14 diseases from a lot of 112,200 images available in the dataset. After the CheXNet [17] model, Benjamin Antin et al.(2017) [18] worked on the same dataset and proposed a logistic regression model for detecting pneumonia. Pulkit Kumar, and Monika Grewal (2017) [19], using the cascading convolutional networks, contributed their research for multilabel classification of thoracic diseases. Zhe Li (2018) [20] recently proposed a convolutional network model for disease identification and localization. Pneumonia detection using CNN and feature extraction was proposed by Dimpsy Varshi (2021), using the convolutional neural network to detect the presence of pneumonia.

III. DATASET DESCRIPTION

The dataset used is ChestX-ray14, released by Wang et al. (2017) [16], also publicly available on the Kaggle [21] platform, which consists of 112,120 frontal chest X-ray images from 30,085 patients. Each radiographic image in the dataset is labeled with one or more out of different thoracic diseases. These labels were concluded through Natural Language Processing (NLP) by text-mining disease classification from the associated radiological reports and areexpected to be more than 90% accurate. For the sake of this work, following the approaches from the past [17], we treat the labels as ground truth for the purpose of pneumonia detection. Prior to the release of this dataset, the largest publicly available dataset of chest radio-graphs was Open [15], which consisted of roughly 4,143 X-ray images. All the radio-graph images in the dataset are of 1024 by 1024 resolution. Out of these 112,120 images, 1431 images are found to be labeled with pneumonia. In order to balance the dataset for binary classification, 1431 normal X-ray images (labeled with 'No Findings') have been selected from the dataset. Altogether, the final dataset used for the classification task is the subset of the original dataset, which consists of 1431 positive image samples (images labeled with 'Pneumonia') and 1431 negative image samples (images labeled with 'No Findings'). After that, the dataset was divided into two parts, out of which for the testing, 573 images were randomly selected from the whole final dataset. The images were downscaled from 1024 by 1024 resolution to 224 by 224 resolution before they were given input to the network.

IV. METHODOLOGY OF PROPOSED MODEL

This section deals with the detailed description of a applied methodology. The image augmentation of the dataset is described in Figure 2. The architecture of the proposed model has been divided into three different stages - the preprocessing stage, the feature extraction stage, and the classification stage.

A. The Pre-processing Stage

Commonly Convolutional Neural Network is used for image classification. Keras Image Data generator is used for getting the input of the original data and further, it makes the transformation of this data on a random basis and gives the output resultant containing only the data that is newly transformed. It does not add the data. Keras image data generator class is also used to carry out data augmentation where we aim to gain the overall increment in the generalization of the model. Operations such as rotations, translations, shearing, scale changes, and horizontal flips are carried out randomly in data augmentation using an image data generator.

B. The Feature-Extraction Stage

Although the features are extracted using variant methods like Convolutional Neural Networks (CNN), every subsequent winning architecture uses more layers in a deep neural network to reduce the error rate. This works for less number of layers, but when we increase the number of layers, there is a common problem in deep learning associated with that called the Vanishing/Exploding gradient.

In order to solve the problem of the vanishing/exploding gradient, this architecture introduced the concept called Residual Blocks. In this network, we use a technique called skip connections. The skip connection connects activations of a layer to further layers by skipping some layers in between. Theadvantage of adding this type of skip connection is that if any layer hurt the performance of architecture then it will be skipped by regularization. So, this results in training a very deep neural network without the problems caused by vanishing/exploding gradient.

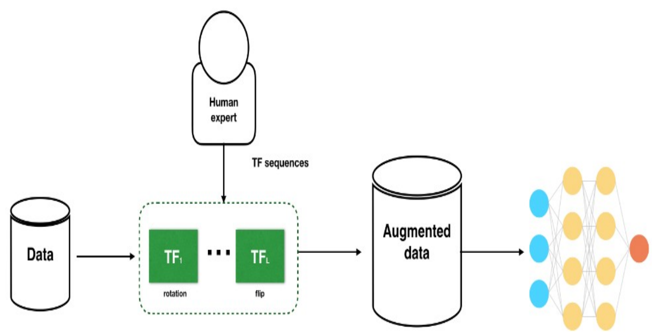

Fig 2, Data augmentation using Keras Image data generator

1) Data Collection

Collecting the dataset for computer-vision (CV) modeling is a crucial work that delineates the objective of inquiry. This investigation meticulously selected relevant data attributes to ensure effective and valid model training. The CV model, aimed at discerning the spatial arrangements of rebar, leverages a diverse range of image features.Additionally, the data collection process incorporated data augmentation, producing more distinctive images for model training. This augmented dataset enhances the model agility and deployment accuracy.

2) Data Augmentation

Data augmentation plays is key in improving the performance and generalization capabilities of imagesegmentation models, particularly in situations where datasets are limited. Herein, four augmentation pipelines were employed to enrich the dataset and mitigate the risk of overfitting.By computing the maximum and minimum pixel intensity values, the pixel values are normalized to enhance the visibility and clarity of objects. Increasing the contrast effectively distinguishes objects of interest from the background, mitigating the impact of noise and artifacts, and ultimately boosting the segmentation accuracy of the model. Lastly, saturation adjustment isutilized to modify the color saturation of the images. By scaling the pixel intensity values, saturation can be increased or decreased, thereby improving the model’s ability to detect and recognize objects by enhancing their visual characteristics.

3) Early Stopping

In machine learning, early stopping is a form of regularization used to avoid overfitting when training a learner with an iterative method, such as gradient descent. Such methods update the learner so as to make it better fit the training data with each iteration. Up to a point, this improves the learner's performance on data outside of the training set. Past that point, however, improving the learner's fit to the training data comes at the expense of increased generalization error. Early stopping rules provide guidance as to how many iterations can be run before the learner begins to over-fit. Early stopping rules have been employed in many different machine learning methods, with varying amounts of theoretical foundation.

V. RESULTS AND DISCUSSION

Figure 3 illustrates the normal chest X-ray and Pneumonia chest X-ray images output. Figure 4 illustrates the graph of learning rate. Chest X-rays dataset taken from Kaggle which contain various x-rays images differentiated by two categories “Pneumonia” and “Normal”. We will be creating a deep learning model which will actually tell us whether the person is having pneumonia disease or not having pneumonia.

Keras is a Python module for deep learning that runs on the top of TensorFlow library. It was created to make implementing deep learning models as easy and fast as possible for research and development.

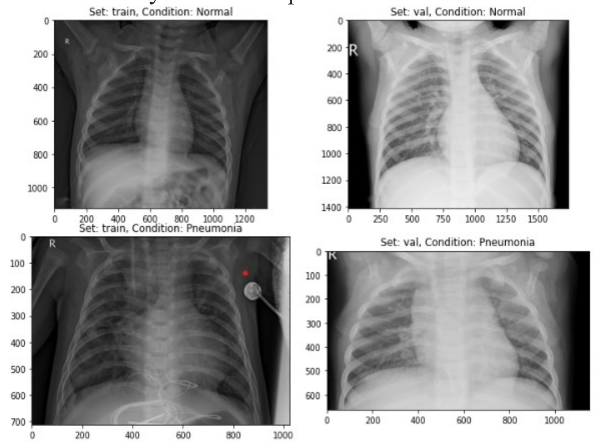

Fig 3, An example of Normal Chest X-ray and Pneumonia Chest X-ray result obtained by the model

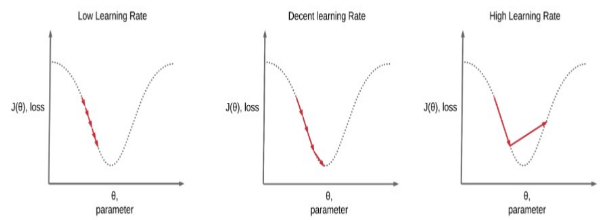

Fig 4, Represents the Reduce LR On Plateau

VI. CONCLUSION

Although the results were overwhelming, there were still some limitations in our model which we believe are vital to keep in consideration. With small data sets, residual neural networks can also lead to over fitting, as the model structure is too complex and cannot be sufficiently learned with the few training instances. The ResNet has some limitations, such as complexity, susceptibility, over fitting and interpretability. The biggest limitation is that there is no history of the associated patient considered in our evaluation model. Our study will likely lead to the development of better algorithms for detecting Pneumonia in the foreseeable future.

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