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Bronchogenic Carcinoma Detection

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ABSTRACT: Pneumonia is one of the major illnesses that account for most fatalities worldwide. Pneumonia can be brought on by fungus, bacteria, or viruses. In order to categorize and identify the presence of pneumonia from a variety of chest X-ray image samples, this research suggests a convolutional neural network model trained entirely from scratch. In order to extract features from a particular chest X-ray image and categorize it to determine whether a person is infected with pneumonia, we built a convolutional neural network model from inception.

KEYWORDS: Pneumonia, X-Ray imaging, CNN, deep learning

I. INTRODUCTION

For many people, particularly in developing countries where billions of people experience energy poverty and depend on polluting forms of energy, the risk of pneumonia is extremely high. According to the WHO, pneumonia and other illnesses linked to household air pollution cause over 4 million premature fatalities each year [1]. Each year, pneumonia affects over 150 million individuals, mostly children under the age of five [2]. Due to the lack of medical resources and personnel in these areas, the issue may worsen. For instance, there is a shortage of 2.3 million physicians and nurses across the 57 countries of Africa [3, 4]. A prompt and correct diagnosis is crucial for these populations. For those who are already having symptoms, it can ensure prompt access to treatment and save desperately needed time and money.

The best imaging modality to detect pneumonia is a chest X-ray (CXR). On the CXR, pneumonia shows up as a region or areas of increased opacity [5]. The automatic analysis and clinical diagnosis of medical images have become increasingly essential applications of deep learning. Convolutional neural network (CNN)-based techniques have been effectively used to categorize diseases, find abnormal regions, and segment lesions in CXR images. [6].

A chest X-Ray is one of the most common medical procedures used to identify the illness. An image is created on the metal surface as the focused beam of electrons, known as x-ray photons, passes through the human tissues. The radiologist will look for white spots in the lungs called infiltrates that indicate an infection when interpreting chest X-rays for pneumonia. When trying to determine whether there is an infected region in the lungs, x-ray images' limited colour palette of black and white causes problems. Such cloudy patterns, however, would also be seen in severe bronchitis instances and TB pneumonitis.

II. RELATED WORK

Latest improvements in deep learning models and the availability of huge datasets have assisted algorithms to outperform medical personnel in numerous medical imaging tasks such as diabetic retinopathy detection [7], arrhythmia detection [8], skin cancer classification [9], haemorrhage identification [10]. These days, interest has grown in chest radiography. These methods are increasingly being used for pulmonary tuberculosis classification [12] and lung nodule detection [11].

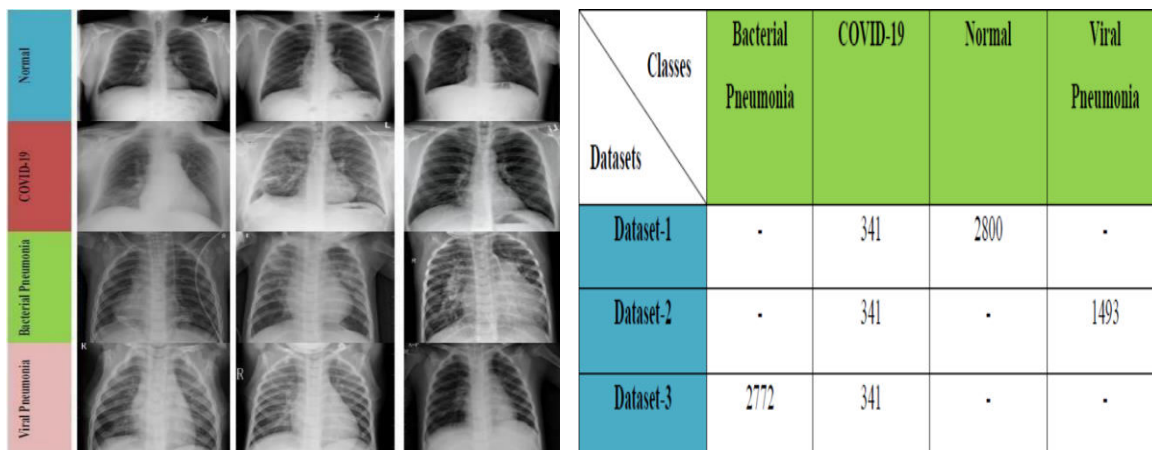
Deep learning methods were implemented by Huang et al. [13]. Islam et al. suggested the performance of various Convolutional Neural Network (CNN) variants for abnormality identification in chest X-rays using the OpenI dataset, which is freely accessible [14]. A larger dataset of frontal chest X-rays was made available by Wang et al. (2017) [15] for the improved exploration of machine learning in chest screening.

Recently, Pranav Rajpurkar, Jeremy Irvin, et al. (2017) [16] explored this dataset for detecting pneumonia at a level better than radiologists, they referred 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. Benjamin Antin et al. (2017) [17] used the same dataset as CheXNet [16] and suggested a logistic regression model for diagnosing pneumonia.

III. METHODOLOGY

1) Dataset Collection:

Three datasets of chest X-Ray images are collected from Kaggle store which consists of different images like bacterial pneumonia, viral pneumonia, COVID19 and normal images. Figure 1(a) shows the different types of images present in the datasets collected. Figure 1(b) displays the classification and count of different type of images in the collected dataset.



1(a)

1(b)

2) Data Pre-processing:

For training, CNN models require input image arrays of the same dimension. When data pre-processing is used, large raw images can be reduced in size, speeding up model training and improving performance.

3) CNN Model:

One of the widely used model for image recognition problems is the Convolutional Neural Network (CNN). In terms of how CNN operates, the images provided as information must be viewed by PCs and transformed into a format that can be produced.

As a result, images are initially converted to framework design. The framework determines which image belongs with which label based on differences between images and subsequently between networks. It determines expectations for new images using them after learning the effects of these differences on the mark during the preparation stage. To effectively carry out these functions, CNN consists of three distinct layers: a convolutional layer, a pooling layer, and a fully associated layer. Both the convolutional layer and the pooling layer contain the element extraction measure. On the other hand, the order cycle occurs in a layer that is fully associated. It consists of three layers that helps in image processing. They are:

- 1) Convolutional layer
- 2) Pooling layer
- 3) Fully Connected (FC) layer



3.1) Convolutional Layer:

The foundational layer of CNN is a convolutional layer. It is responsible for selecting the example's features. The information image is passed through a channel in this layer. The element map is made up of the characteristics obtained through sorting. A 3x3 or 5x5 formed grid that can be altered using the information design network makes up the part. The number of steps tuned for moving over an input structure is known as the step boundary. Convolutional layer output can be expressed as:

$$x_j^l = f \left(\sum_{a=1}^N w_j^{l-1} * y_a^{l-1} + b_j^l \right)$$

where x_j^l is the j -th include map in layer l , w_j^{l-1} demonstrates j -th bits in layer $l-1$, y_a^{l-1} addresses the a -th highlight map in layer $l-1$, b_j^l shows the inclination of the j -th include map in layer l , N is number of absolute highlights in layer $l-1$, and $(*)$ addresses vector convolution measure.

3.2) Pooling Layer:

The pooling layer comes next after the convolutional layer. By using a numerical comparison, a pooling layer is typically added to component maps to reduce the number of highlight guides and organizational boundaries. We used both global normal pooling and max-pooling in this investigation. Reduced yield neurons result from the maximum pooling measure's selection of only the highest value using each component map's specified framework size. A global normal pooling layer that reduces information to a single size is also present and is only used prior to the fully associated layer. It is connected to the fully connected layer that comes after the global normal pooling layer.

3.3) Fully Connected (FC) Layer:

The final and most important layer of CNN is called the Fully Connected (FC) layer. This layer has multi-facet perceptron-like capabilities. On the Fully Connected layer, Corrected Linear Unit (ReLU) enactment work is typically used, whereas SoftMax initiation work is used to predict yield images in the final layer of the Fully Connected layer. FC layer output can be expressed as:

$$ReLU(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases}$$

$$Soft\ max(x_i) = \frac{e^{x_i}}{\sum_{y=1}^m e^{x_y}}$$

where x_i and m address input information and the quantity of classes individually.

4) Binary Classification:

Sophisticated CNN-based models like ResNet50, ResNet101, ResNet152, InceptionV3 and Inception-ResNetV2 models are used for the classification of COVID-19 Chest X-beam images into three different binary classes.

COVID-19 and normal images fall under Binary Class 1. COVID-19 and virus pneumonia fall under Binary Class 2, while COVID-19 and bacterial pneumonia fall under Binary Class 3. The CNN consists of pre-trained models like ResNet50, ResNet101, ResNet152, InceptionV3 and Inception ResNetV2 for the successful detection of normal, COVID-19, bacterial and viral pneumonia cases.

IV. EXPERIMENTAL RESULTS

1) Upload Image:

The image upload webpage is used to upload jpg images for both CT scan and X-Ray images. The website has two options: the first is for uploading X-Ray images, and the second is for transferring CT Scan images. In the database, all



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images were downsized to 224x224 pixels. Individual chest X-Ray images of individuals with common cold, COVID-19, bacterial, and viral pneumonia are provided.



1(a)

2) Prediction Result of X-Ray Images:

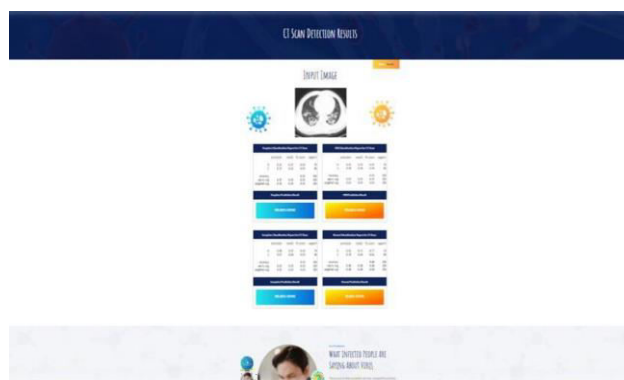
Once the X-Ray image is uploaded, the result prediction webpage displays the outcome of an X-Ray image transfer. It analyzes the image, predict the exactness using sophisticated learning calculations, and highlight the outcomes of the affected patient.



1(b)

3) Prediction Result of CT Scan Images:

Once the CT scan image is uploaded, the result prediction webpage forecasts the outcome of a CT scan image and breaking down the image and calculates the precision through deep learning calculations, as well as feature the outcome of the affected patient.



1(c)

V. CONCLUSION

Forecasting COVID-19 casualties is critical to preventing the disease from spreading to others. In this study, I suggested a deep exchange learning-based methodology for naturally anticipating COVID-19 patients using Chest X-beam images obtained from normal, COVID-19, bacterial, and viral pneumonia patients. The execution results indicate that the ResNet50 pre-prepared model produced the highest precision among five models for three distinct datasets (Dataset-1: 96.1%, Dataset-2: 99.5%, and Dataset-3: 99.7%).

With the help of CNN, it is widely assumed that it will aid radiologists in making clinical practice decisions for the best. This examination provides understanding on how profound exchange learning methods can be used to identify COVID-19 at an early stage.

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