LUNG X-RAY IMAGE ENHANCEMENT TO IDENTIFY PNEUMONIA WITH CNN

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ABSTRACT

Pneumonia is a life-threatening infectious disease affecting one or both lungs in humans commonly caused by bacteria called Streptococcus pneumonia. COVID19 can cause severe pneumonia and is estimated to have a high impact on the healthcare system. Early diagnosis is crucial for the correct treatment to possibly reduce the stress in the healthcare system. Pneumonia has caused significant deaths worldwide, and it is a challenging task to detect many lung diseases such as atelectasis, cardiomegaly, lung cancer, etc., often due to limited professional radiologists in hospital settings. The standard image diagnosis tests for pneumonia are chest X-ray (CXR) and computed tomography (CT) scan. Although CT scan is the gold standard, CXR is still useful because it is cheaper, faster, and more widespread. Chest X-Rays which are used to diagnose pneumonia need expert radiotherapists for evaluation. Thus, developing an automatic system for detecting pneumonia would be beneficial and it can save lots of people's lives and help to stop and cure, control a treat the disease without any delay, particularly in remote areas. Due to the success of deep learning algorithms in analyzing medical images, Convolutional Neural Networks (CNNs) have gained much attention for disease classification. In addition, features learned by pre-trained CNN models on large-scale datasets are much useful in image classification tasks. In this work, we appraise the functionality of pre-trained CNN models utilized as feature extractors followed by different classifiers for the classification of abnormal and normal chest X-Rays. We analytically determine the optimal CNN model for the purpose. Statistical results obtained demonstrate that pre-trained CNN models employed along with supervised classifier algorithms can be very beneficial in analyzing chest X-ray images, specifically to detect Pneumonia. This study aims to identify pneumonia caused by other types and also healthy lungs using only X-Ray images. Keywords: X-Ray, CXR, COVID-19, Chest X-ray images, pneumonia detection; convolutional network (CNN), image enhancement.

Keywords: *Pneumonia, diagnosis, cardiomegaly, tomography, CXR, CNN*

I. INTRODUCTION

Pneumonia is an infectious and deadly illness in the respiratory that is caused by bacteria, fungi, or a virus that infects the human lung with a load full of fluid or pus. Chest X-rays are the common method used to diagnose pneumonia and it needs a medical expert to evaluate the result of the X-ray. The troublesome method of detecting pneumonia cause a life lost due to improper diagnosis and treatment. And the diagnosis of these diseases can take time to do that and hospitals must have good radiologist but in our country, we can't afford it. So we must go to the automated system. With the emerging computer technology, the development of an automatic system to detect pneumonia and treat the disease is now possible especially if the patient is in a distant area and medical services are limited. Pneumonia is a lung parenchyma inflammation often caused by pathogenic microorganisms, factors of physical and chemical, immunologic injury, and other pharmaceuticals. There are several popular pneumonia classification methods: (1) pneumonia is classified as infectious and noninfectious based on different pathogeneses in which infectious pneumonia is then classified as bacteria, virus, mycoplasmas, chlamydial pneumonia, and others, while non-infectious pneumonia is classified as immune-associated pneumonia, aspiration pneumonia caused by physical and chemical factors, and radiation pneumonia. (2) Pneumonia is classified as CAP (community-acquired pneumonia), HAP (hospital-acquired pneumonia), and VAP (ventilator-associated pneumonia) based on different infections, among which CAP accounts for a larger part. Because of the different range of pathogens, HAP is easier to develop resistance to various antibiotics, making treatment more difficult. Pneumonia kills more than 800,000 children under five per year, with around 2200 deaths every day. There are more than 1400 children infected with pneumonia per

100,000 children. The Global Burden of Disease Study reported that lower respiratory tract infections, including pneumonia, were the second largest cause of death in 2013. In Europe, nearly 35.

II. LITERATURE REVIEW

• Many researchers have contributed to this field. Various combinations of existing technologies have been used.

• In 2016, Redmon et al. proposed YOLO, which does not require a separate region proposal network, so its detection speed is extremely fast and can reach 45FPS. In the same year, Liu et al. [11] proposed the SSD algorithm. Both SSD and YOLO win in detection speed, but SSD uses a multiscale feature map to detect independently, the spatial resolution of images in deep networks has been significantly reduced, and it may not be possible to locate small targets that are difficult to detect in low resolution, reducing the accuracy of detection. YOLO does not use multiscale feature maps for independent detection. It smoothes the feature map and splices it with another lower-resolution feature map, but it treats the detection only as a regression problem and the detection accuracy is low. In 2014, Girshick et al. proposed R-CNN, which greatly improved the speed of training. On the PASCAL VOC 2010 dataset, the mAP improved from 35.1

• In 2018, Lee et al. proposed DetNet, which was designed specifically for target detection and achieved better detection results with fewer layers. To avoid the large computational complexity and memory consumption caused by the high-resolution feature map, the network adopts a low-complexity dilated bottleneck structure; a higher resolution of the feature map is ensured while obtaining a higher subtractive field. This paper draws on the idea of DetNet and the framework of Faster R-CNN to study the detection of pneumonia. [2]

• In recent years, many scholars have made efforts to detect pneumonia. Abiyev and Ma'aitah apply a convolutional neural network (CNN) for the diagnosis of chest X-ray diseases. Compared to BPNN and RNN, CNN gets higher precision but longer training time. Vijendran and Dubey combine multilayer extreme learning machine (MLELM) and online sequential extreme learning machines (OSELM) to detect pneumonia on the chest X-ray image. Abiyev and Ma'aitah explore the features extracted from layers of the CNN along with a set of classical features, including GIST and bag of words on a dataset of more than 600 radiographs [3]

• Chowdhury et al. worked with chest X-ray images to develop a novel framework named PDCOVIDNet based on parallel-dilated CNN. In the proposed method, the authors used a dilated convolution in the parallel stack that could capture and stretch necessary features for obtaining a detection accuracy of 96.58

• Abbas et al. proposed and validated a deep convolutional neural network called decompose, transfer, and compose (DeTraC) to detect COVID-19 patients from their chest X-ray images. They proposed a decomposition mechanism to check irregularities from the dataset by investigating class boundaries for obtaining a high accuracy.

• Data Collection Data is collected from Kaggle.com whuch is the biggest datasource now a days for analysis and machine learning data you needto do your data science work. Use over 50,000 public datasets .Ifanyone working with data for machine learning then kaggle.comwill be the primary choices.

• The Pre-Processing Stage The primary goal of using Convolutional Neural Network inmost of the image classification tasks is to reduce thecomputational complexity of the model which is likely toincrease if the input are images . The original 1-channelblack and white images were resize from 1024×1024 into224×224 pixels to reduce the heavy computation and forfaster processing. All of the further techniques has beenapplied over these downsized images.in prepossessing wemust reject incomplete data or lebel all any type of problemthat is not working with the model success.and we also needto take only valid and updated value.

• The Feature-Extraction Stage Although, the features were extracted with different variantsof pre-trained CNN models the statistical results obtainedproposed DenseNet-169 as the benchmark model for thefeature extraction stage. Therefore, this stage deals with thedescription of DenseNet-169 .When we make our ownmodel we will compare it with the benchmark model andhow efficient and accurate it is.Since CNN can do thefeature extraction easily we can do that with multiple CNNwith different feature combination.

• Architecture of our proposed model We Use DNN (Deep Convolution Neural Network) whichhas become the most productive framework in this field.

1. Collect The Data: Data will be collected from the kaggle.com and with validform of data and data should have sized 1024x1024.Data Size will be almost 1.5 gigabyte depending on theupdate of the data set.

2. Reshape the data: Since it is public data set there might be some form ogglitch.so we need to handle it.and to increase the processingtime we down sample the data.Since we have plenty ofimage we will directly discard the data. Then we reshape thedata so our model will be done better.

3. Feed the Classification Model: In this model we do not apply Transfer learning, we split thedata 80

III. METHODOLOGY

CNN models have been created from scratch and trained on Chest X-Ray Images (Pneumonia) dataset on Kaggle. Keras neural network library with TensorFlow backend has been used to implement the models. Dataset consists of 5216 training images, 624 testing images and 16 validation images. Data augmentation has been applied to achieve better results from the dataset. The four models have been trained on the training dataset, each with different number of convolutional layers. Each model was trained for 20 epochs, with training and testing batch sizes of 32 and 1, respectively. The following sub-headings further explain the above stages in depth.

IV. EXISTING SYSTEM

The main diagram of our existing full system. As seen in this figure, the system is composed of several steps including the Data collection and preprocessing description, building the classification models, and extracting the required features. These steps can be divided into four phases: Data Set, data preprocessing, building and validating classification models, and feature extraction.

• Data Collection The chest x-ray image dataset is available at [15]. It was the Chest X-Ray images which include normal chest X-Ray and Pneumonia chest X-Ray. Here, we have taken 5,856 sample images of the dataset to use later on for recognition and classification of pneumonia.1,583 of which are normal X-Ray lung images, and 4,273 of which are X-Ray lung images with Pneumonia from patients. These data set was used for training in deep learning method and testing data using ”Pandas” for predicting Pneumonia.The X-ray images were divided into train, test, and validation groups. 80

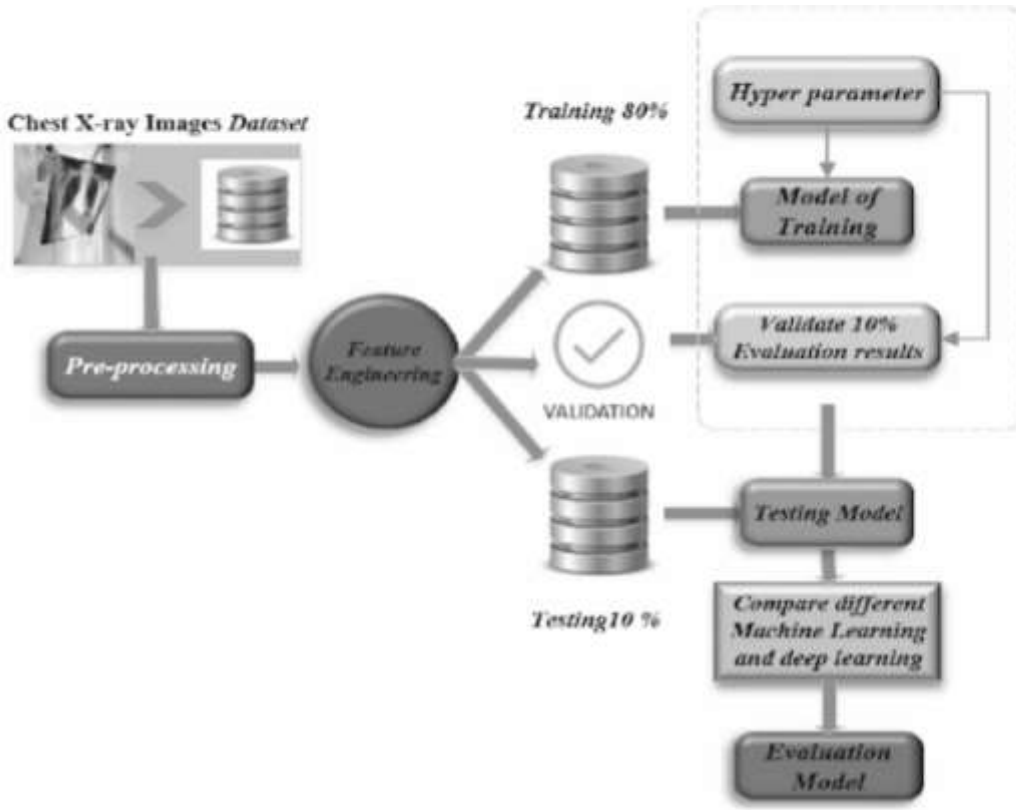

Figure 4.1: Existing System Architecture

• Data Prepossessing The most important part of machine learning is data and data must be clean for models to process it. When it comes to image data, there are some preparation methods. Various types of pre-processing tasks such as dimension reduction, image resize, and image cropping is applied. Depending on the original data sets, it showed several problems that need to be addressed before image classification. First, resize the image to the same size as the original image. The image can be resized to get rid of unnecessary information in the background The raw images have different image sizes one from another. The machine learning model requires the data being trained must have the same size. Next, observing the X-Ray image samples, most samples were two-dimensional image, while a few samples were threedimensional image.The two preprocessing approaches mentioned above (resizing and dimension reduction) were the most important for preprocessing because of the unequal data dimensions. Other pre-processing approaches were also used on individual images samples whose quality was out of control.

V. PROPOSED SYSTEM

In this research, the proposed approach relies on transfer learning and investigates state-of-the-art pretrained CNN models to overcome the image-based pneumonia classification problem. In addition, data augmentation is also deployed to improve the deep learning model generalization and address the overfitting problem. In fact, the Deep Residual Learning for Image Recognition [17] was originally proposed to solve the gradient vanishing problem faced by CNN based architectures. In other words, the residual connections are intended to prevent information loss that may happen when training the deep networks. This yielded deeper layers for ResNet [21] compared to VggNet [17] and AlexNet [14].
On the other hand, the feature reusability can be achieved using DenseNet. Particularly, the resulted condensed model is intended to be easily trainable and less complex. In fact, every layer in DenseNet takes

additional inputs from all previous layers and passes on its feature-maps to all following layers [7]. Figure 2 illustrates how we reduce the model size and complexity, by implementing BN-ReLU-1×1 Conv first then BN-ReLU-3×3 Conv.In this research, we consider DenseNet169 which achieved promising performance on several applications.

As one can see, DenseNet can be perceived as a directed acyclic graph CNN (DAGCNN) that overcomes the vanishing gradient problem and allows information transfer flow between the network layers. Literally, it contains direct connections from any layer to all following layers as illustrated in Figure 3. In particular, every two adjacent blocks are separated by a transition layer which changes the feature map size through convolution and pooling operations. The design of the proposed end-to-end model based using DensNet requires the specification of the number of convolution layers in each dense block to guarantee efficient information flow. Similarly, the number of dense blocks will be determined empirically. Furthermore, different optimization techniques will be investigated in this research.

Training the proposed deep networks which involve millions of parameters from scratch would take weeks. Moreover, this requires big data to avoid overfitting, and powerful Graphics Processing Units (GPUs) resources.

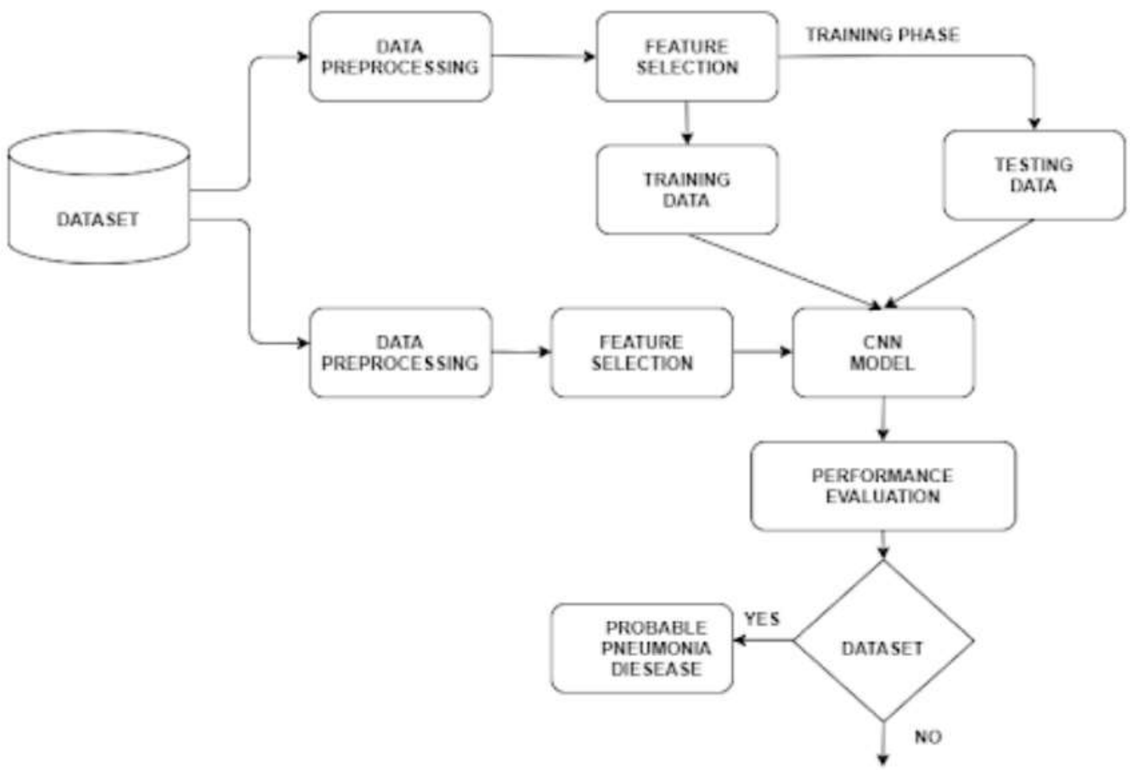

Figure 5.1: Block Diagram

VI. APPLICATION

The application that will be developed is going to be useful to the many systems.

- 1. Used to detect Pneumonia at early stage.
- 2. Medical System.

VII. CONCLUSION

In this paper, study describes a CNN-based model aiming to diagnose pneumonia on a chest X-ray image set. This will help our early detection of pneumonia quickly. Our project successfully provides with a CNN based approach for detection of pneumonia automatically.

VIII. FUTURE SCOPE

In the data set there are small boxes indicating the presence of pneumonia in future one can use these bounding boxes to train the CNN to not only classify image with pneumonia but also to identify where is pneumonia in a person's chest.

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