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PNEUMONIA CATEGORIZATION USING DEEP LEARNING

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Abstract

Pneumonia poses a significant threat to human life, affecting the lungs and often caused by Streptococcus pneumoniae bacteria. In India, pneumonia is a leading cause of mortality, responsible for one in three deaths, according to the World Health Organization (WHO). Diagnosing pneumonia typically involves chest X-rays, which require skilled radiologists for interpretation. However, this expertise may not be readily available, especially in remote areas. Therefore, there is a pressing need to develop automated systems for pneumonia detection to expedite treatment, particularly in underserved regions.

Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for analyzing medical images. Leveraging pre-trained CNN models, which have learned features from extensive datasets, holds promise for accurate disease classification. In this study, we aim to develop and evaluate several CNN models for the classification and identification of pneumonia from lung X-ray images.

Keywords: Convolutional Neural Networks, Bacterial Pneumonia, Viral Pneumonia, Normalization, Augmentation.

1. INTRODUCTION

The urgency and significance of this project cannot be overstated. Pneumonia remains a leading cause of mortality worldwide, particularly among vulnerable populations. Conventional diagnostic methods can be time-consuming and error-prone, often leading to delays in critical treatments. Machine learning techniques offer the potential to revolutionize pneumonia detection by providing rapid and accurate assessments of X-ray images. However, past failures underscore the complexity of this challenge, highlighting the critical need for a comprehensive approach that encompasses training with diverse data, differentiation between viral and bacterial pneumonia, and the utilization of effective normalization and augmentation techniques. By developing an open-source web tool that integrates these solutions, we are not only advancing medical technology but also democratizing access to a life-saving resource. This project's success would bridge the gap between state-of-the-art AI and medical practice, potentially saving countless lives and heralding a new era of timely and precise pneumonia diagnosis. The gravity of this endeavor lies in its potential to transform healthcare outcomes on a global scale.

2. RELATED WORK

Recently, there has been growing interest in utilizing Machine Learning (ML) algorithms for detecting thoracic diseases in medical image classification research. Lakhani and Sundaram (2017) [1] introduced a method for detecting pulmonary tuberculosis by employing two different Deep Convolutional Neural Networks (DCNNs), namely AlexNet and GoogleNet. Huang et al. [2] also utilized deep learning techniques for lung nodule classification, primarily for diagnosing lung cancer. Islam et al. [3] proposed the use of various Convolutional Neural Network (CNN) variants for abnormality detection in chest X-rays, leveraging the publicly available OpenI dataset [4].

To further advance machine learning applications in chest screening, Wang et al. (2017) [5] released a larger dataset of frontal chest X-rays. Subsequently, Pranav Rajpurkar, Jeremy Irvin, et al. (2017) [6] utilized this dataset to develop the ChexNet model, which surpasses radiologists in detecting pneumonia and other diseases using a DenseNet-121-layer architecture. Building upon this, Benjamin Antin et al. (2017) [7] proposed a logistic regression model specifically for detecting pneumonia on the same dataset.

Additionally, Pulkit Kumar and Monika Grewal (2017) [8] contributed to the field by employing cascading convolutional networks for multilabel classification of thoracic diseases. More recently, Zhe Li (2018) [9] introduced a convolutional network model for disease identification and localization.

3. DATASET DESCRIPTION

The dataset used is Chest X-Ray Images (Pneumonia) released by HOMAYOON KHADIVI (2022) also publicly available on the Kaggle platform which consists of 5856 chest X-ray images. The dataset used is Chest X-Ray Images (Pneumonia) released by ESBEN MALM (2021)also publicly available on the Kaggleplatform which consists of 5278 chest X-ray images.

4. METHODOLOGY OF PROPOSED MODEL

This section deals with the detailed description of the applied methodology. The proposed pneumonia detection system using the 'Convolutional Neural Network'. The architecture of the proposed model has been divided into different stages - the Preprocessing stage, the Normalizing and Augmentation stage, Generating and training the model stage.

A.The Pre-Processing Stage: The primary goal of using Convolutional Neural Network in most of the image classification tasks is to reduce the computational complexity of the model which is likely to increase if the input are images. The original images were resized from various sizesinto 150x150 pixels to reduce the heavy computation and for faster processing. All of the further techniques have been applied over these downsized images.

B. Normalizing and Augmentation stage: Next, we perform some Data Preprocessing and Data Augmentation before we can proceed with building the model.

We perform a grayscale normalization to reduce the effect of illumination's differences. Moreover, the CNN converges faster on [0.1] data than on [0.255].

In order to avoid overfitting problem, we need to expand artificially our dataset. We can make your existing dataset even larger. The idea is to alter the training data with small transformations to reproduce the variations. Approaches that alter the training data in ways that change the array representation while keeping the label the same are known as data augmentation techniques. Some popular augmentations people use are grayscales, horizontal flips, vertical flips, random crops, color jitters, translations, rotations, and much more. By applying just, a couple of these transformations to our training data, we can easily double or triple the number of training examples and create a very robust model. For the data augmentation, Ichooseto:

i. Randomly rotate some trainingimages by 30 degrees
ii. Randomly Zoom by 20% sometraining images
iii. Randomly shift images horizontallyby 10% of the width
iv. Randomly shift images vertically by10% of the height

Randomly flip images horizontally. Once our model is ready, we fit the training dataset.

C. Generating and training the model stage:

While generating the model the following layers are added into the model:

Input Layer:

- Input shape: (150, 150, 1) indicating a grayscale image with a resolution of 150x150 pixels.

Convolutional Layers:

- The first convolutional layer has 32 filters of size (3,3) with a stride of 1 and same padding. ReLU activation is applied after convolution.
- The second convolutional layer has 64 filters of size (3,3) with a stride of 1 and same padding. ReLU activation is applied after convolution.
- The third convolutional layer also has 64 filters of size (3,3) with a stride of 1 and same padding. ReLU activation is applied after convolution.
- The fourth convolutional layer has 128 filters of size (3,3) with a stride of 1 and same padding. ReLU activation is applied after convolution.
- The fifth convolutional layer has 256 filters of size (3,3) with a stride of 1 and same padding. ReLU activation is applied after convolution.

Batch Normalization:

- Batch normalization is applied after the first, second, third, and fourth convolutional layers. This helps in normalizing the activations of each

layer, which can speed up training and improve convergence.

Max Pooling Layers:

- After each convolutional layer, max-pooling is applied with a pool size of (2,2), a stride of 2, and same padding. This reduces the spatial dimensions of the feature maps while retaining important features.

Dropout Layers:

- Dropout with a rate of 0.1 is applied after the second convolutional layer.
- Dropout with a rate of 0.2 is applied after the fourth and fifth convolutional layers, as well as after the first fully connected layer. Dropout helps in reducing overfitting by randomly dropping a fraction of the neurons during training.

Flatten Layer:

- Before passing the features to the fully connected layers, the feature maps are flattened into a vector.

Fully Connected Layers:

- There is one fully connected layer with 128 units and ReLU activation.
- The output layer consists of one unit with sigmoid activation, suitable for binary classification tasks.

Compilation:

- The model is compiled using the RMSprop optimizer and binary cross-entropy loss function.
- Accuracy is chosen as the evaluation metric.

While training the model with normal and pneumonia images at 12 epochs:

Epoch	Learning Rate	Accuracy
1.	0.0010	0.8482
2.	0.0010	0.9024
3.	0.0010	0.9195
4.	0.0003	0.9475
5.	0.0003	0.9502
6.	0.0003	0.9530
7.	0.0003	0.9557
8.	0.00009	0.9548
9.	0.00009	0.9643
10.	0.00009	0.9649
11.	0.000027	0.9689
12.	0.000027	0.9684

While testing the date with unknown data instead of validation data at each step the actual accuracy of the model is 91.34%.

Similarly, while training another model with viral pneumonia and bacterial pneumonia images:

Epoch	Learning Rate	Accuracy
1.	0.0010	0.6317
2.	0.0010	0.6899
3.	0.0010	0.7103
4.	0.0010	0.7172
5.	0.0010	0.7144
6.	0.0010	0.7301
7.	0.0010	0.7262
8.	0.0010	0.7327
9.	0.0010	0.7286
10.	0.0010	0.7242
11.	0.0010	0.7430
12.	0.0010	0.7378
13.	0.0010	0.7450
14.	0.0010	0.7399
15.	0.0010	0.7505
16.	0.0010	0.7463
17.	0.0010	0.7507
18.	0.0010	0.7571
19.	0.0010	0.7533
20.	0.0010	0.7620
21.	0.0010	0.7600
22.	0.0010	0.7600
23.	0.0010	0.7620
24.	0.0010	0.7613

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While testing the date with unknown data instead of validation data at each step the actual accuracy of the model is 86.74%.

The Prediction of the image result is explained by the below diagram (1):

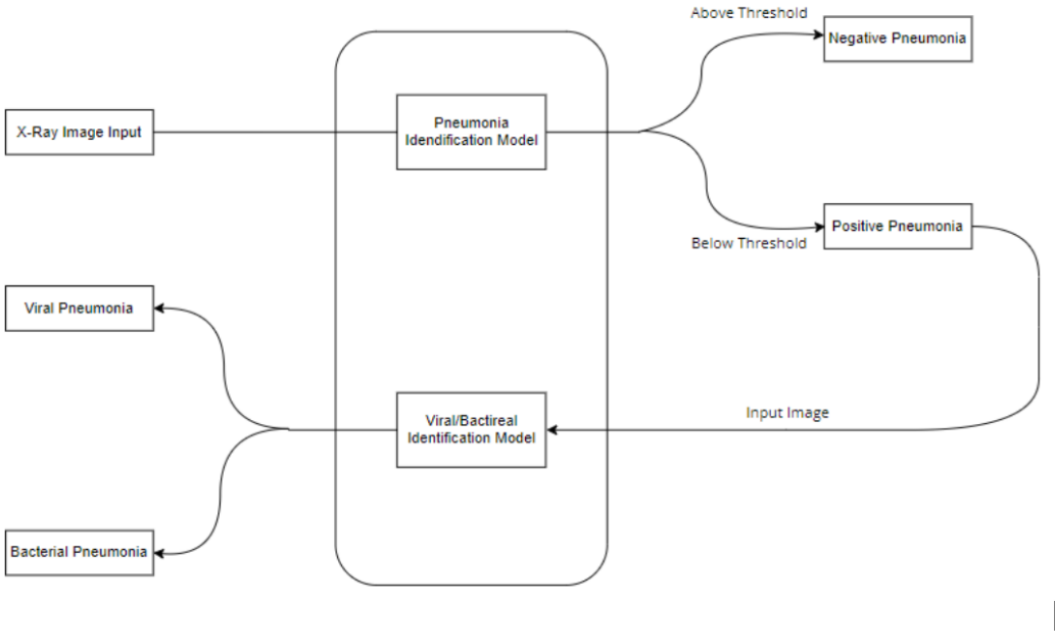

Fig 1. Flow of image data while calculation of result.

Pneumonia Detection Model:

● Upon receiving an X-ray image as input, the Machine Learning (ML) model, trained on pneumonia and normal X-rays, determines whether the image exhibits pneumonia or not.

Secondary Classification:

● In cases where pneumonia is identified, the system proceeds to a secondary ML model. This model specializes in distinguishing between viral and bacterial pneumonia based on specific training on viral and bacterial X-ray lung images.

5. CONCLUSION

Presence of expert radiologists is the topmost necessity to properly diagnose any kind of thoracic disease. This paper primarily aims to improve the medical adeptness in areas where the availability of radiotherapists is still limited. Our study facilitates the early diagnosis of Pneumonia to prevent adverse consequences (including death) in such remote areas. So far, not much work has been contributed to specifically to detect Pneumonia from the mentioned dataset. The development of algorithms in this domain can be highly beneficial for providing better health-care services.

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[11] Some parts are taken from IEEE Explore Paper called “Pneumonia Detection Using CNN based Feature Extraction” by Dimpy Varshni; Kartik Thakral; Lucky Agarwal; Rahul Nijhawan; Ankush Mittal, since the research is similar, therefore the related work.