Pneumonia Detection in Chest X-Rays: An Analysis of Convolutional Neural Networks

J Karthik Reddy , Dr. Virendra Singh Kushwah[1]

Abstract

This study introduces a novel approach to pneumonia detection in chest X-ray images by proposing a convolutional neural network (CNN) model trained from scratch. Our approach to achieving a remarkable classification performance is different from other methods that only use handcrafted techniques or transfer learning approaches. Instead, we built a convolutional neural network model from scratch that can extract features from a given chest X-ray image and classify it to determine if a person has pneumonia. The reliability and interpretability issues that arise regularly while working with medical images may be addressed with the use of this model. For this classification work, it is challenging to gather a big quantity of pneumonia dataset, in contrast to other deep learning classification challenges with important picture repository; hence, we applied multiple data augmentation strategies to improve the CNN model's classification and validation performance and get remarkable validation accuracy.

1. Introduction

Pneumonia poses a serious threat to world health, with large morbidity and death rates, especially in susceptible groups including children, the elderly, and those with weakened immune systems. In order to effectively manage pneumonia, a timely and correct diagnosis is essential. This enables the rapid implementation of suitable treatment options.

A crucial component in confirming the presence of pneumonia has been the use of medical imaging, especially chest X-rays. Radiologists have historically been the experts in visual interpretation of these pictures, but the complexity of image processing and the growing need for healthcare services have prompted the investigation of automated techniques. Deep learning algorithms known as Convolutional Neural Networks (CNNs) have shown impressive performance in image identification tests, suggesting that they might be a viable option for improving the effectiveness and precision of pneumonia diagnosis in chest X-rays.

With a focus on pneumonia identification in chest X-rays, this study intends to examine CNNs in detail and provide a thorough evaluation of their advantages, disadvantages, and capabilities. This project aims to improve patient outcomes and lessen the strain on healthcare systems by utilizing deep learning to support continuing efforts to create strong and trustworthy tools for the early and accurate detection of pneumonia. The current state of pneumonia diagnosis, CNNs' use in medical image analysis, and the main goals and methods used in this study will all be covered in the parts that follow.

2. LITERATURE REVIEW:

This paper presents a convolutional neural network (CNN) model developed from scratch as an original technique for pneumonia diagnosis in chest X-ray images. Unlike existing approaches that mostly depend on transfer learning or conventional methods, our CNN is designed to automatically extract features from images of chest X-rays with the goal of addressing issues with interpretability and reliability in medical imaging. Because there aren't many large databases available for pneumonia, we use data augmentation strategies to improve the model's validation and classification accuracy, with some noteworthy outcomes. Unlike transfer learning-based methods, the article successfully classifies positive and negative pneumonia cases using the CNN model that was created from scratch. The study's conclusion outlines the model's future prospects, including how to improve its capacity to identify and categorize X-ray pictures that show pneumonia. By solving the important problem of pneumonia this reflects a forward-looking strategy to support continued advancements in medical image processing.

3. Materials and Methods

3.1. Dataset

The dataset employed in this research consists of 5840 chest X-ray images, featuring 4265 cases of pneumonia and 1575 normal cases. To facilitate effective training and robust evaluation of our Convolutional Neural Networks (CNNs) for pneumonia detection, we partitioned the dataset into a training set of 5216 images and a testing set of 624 images. It's important to note that the substantial size of the dataset, approximately 1GB in total, may result in extended processing times.

3.2. Preprocessing and Augmentation

In the preprocessing and augmentation phase of this study, the employed methodology utilizes the Keras Image Data Generator, a powerful tool for real-time data augmentation during model training. For the training dataset, the images are rescaled

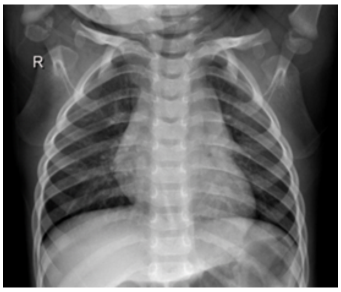

Figure 1: Sample images without pneumonia

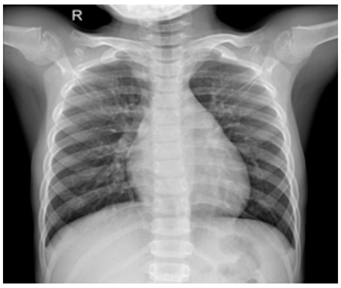

Figure 2: Sample images without pneumonia

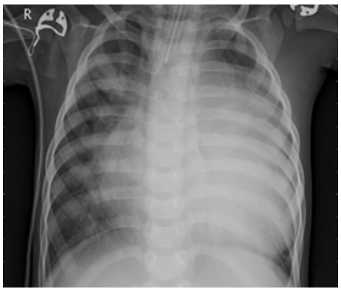

Figure 3: Sample images with pneumonia

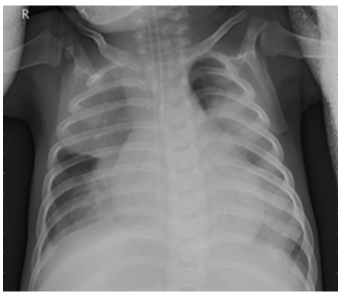

Figure 4: Sample images with pneumonia

Table 1: Settings for the image augmentation

Method	Setting
Rescale	1/255
Rotation range	15
Width shift	0.1
Height shift	0.1
Shear range	0.2
Zoom range	0.2
Horizontal flip	True

to a range between 0 and 1. The augmentation process introduces variability by randomly rotating images within a range of 15 degrees, shifting them horizontally and vertically by 0.1, applying a shear transformation with a range of 0.2, randomly zooming by 0.2, and horizontally flipping the images. These augmentations aim to enhance the robustness and generalization ability of the Convolutional Neural Networks (CNNs) by exposing the model to a diverse range of variations in the training data.

Concurrently, the testing dataset undergoes rescaling only, ensuring consistency in normalization between the training and testing phases. The Keras function facilitates the generation of augmented image batches, streamlining the feeding of data into the CNN model during training and evaluation. The target size and batch size parameters are set to adhere to the requirements of the model, and the classmode is specified as 'binary' since this is a binary classification task, distinguishing between pneumonia-affected and normal chest X-rays. The shuffle parameter is appropriately configured to maintain the order of images during testing for accurate evaluation.

3.3. Model

In the proposed convolutional neural network (CNN) model, the classifier is positioned at the far end. It is essentially a thick layer, often known as an artificial neural network (ANN). Like any other classifier, this one need separate features, or vectors, in order to execute calculations. As a result, a 1D feature vector for the classifiers is generated from the feature extractor's (the CNN portion) output. The output of the convolution operation is flattened in this step, which is called flattening, to produce a single, long feature vector that the dense layer can use for its final classification. A flattened layer, a size 0.5 dropout, two dense layers with sizes 512 and 1, respectively, a RELU in between the two dense layers, and a sigmoid activation function that performs the classification tasks. a pre-trained VGG16 model, well-established for its effectiveness in image classification tasks, is utilized as the foundational architecture. This pre-trained model is initialized with weights from the ImageNet dataset, enabling it to capture intricate features from a wide array of images. The model is configured to exclude the fully connected layers and to accept input images of size (224, 224, 3). To tailor this pre-trained model to the specific task of pneumonia detection in chest X-rays, a custom classification head is appended. The sequential model is extended with a Flatten

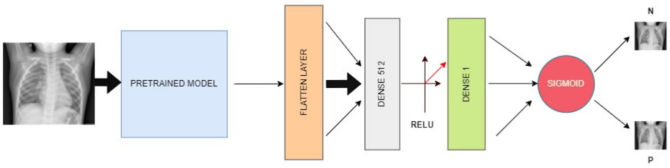

Figure 5: The proposed Architecture.

Table 2: The output of the proposed network architecture

Layer(type)	Output Shape	Param
vgg16 (Functional)	(None, 7, 7, 512)	14714688
Flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 512)	12845568
dropout (Dropout)	(None, 512)	0
dense1(Dense)	(None, 1)	513
=========	=========	==========
Total params	27560769	(105.14 MB)
Trainable params	27560769	(105.14 MB)
Non-trainable params	0	(0.00 Byte)

layer, which transforms the spatial dimensions of the convolutional feature maps into a one-dimensional array. Subsequently, a densely connected layer with 512 units and ReLU activation is introduced to capture complex patterns in the learned features. To mitigate overfitting, a Dropout layer with a dropout rate of 0.5 is incorporated. The final layer consists of a single neuron employing a sigmoid activation function, facilitating binary classification—indicating the presence or absence of pneumonia. The entire model is then compiled using the binary crossentropy loss function, indicative of binary classification tasks. The Adam optimizer is employed with a specified learning rate, and the model's performance is evaluated using accuracy as the metric. This comprehensive architecture, combining the power of a pre-trained VGG16 model with a customized classification head, forms the basis for the subsequent training and evaluation phases in the context of pneumonia detection in chest X-ray images.

4. Results

In the training phase of our pneumonia detection model, the compiled architecture is trained on the provided dataset using the fit method. The training process involves iterating through the training generator, which dynamically generates batches of augmented images. The number of training epochs, specified as a hyperparameter, dictates how many times the model undergoes the entire training dataset. During training, the model refines its weights and biases to learn discriminative features for accurate pneumonia classification. The validation dataset, generated, is used to assess the model's performance on unseen data after each epoch, providing insights into potential overfitting or generalization issues.

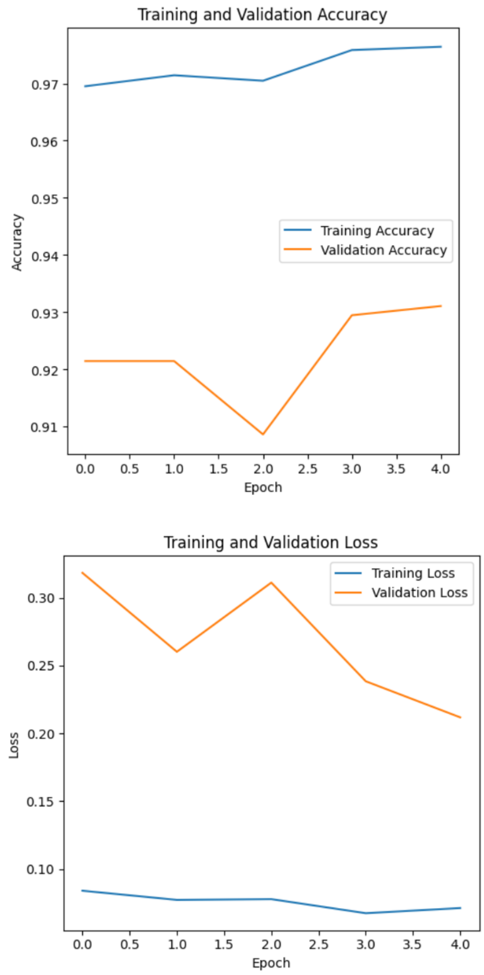

Figure 6: Performance of the classification model on 224 ×224×4 data size.

Following the training phase, the model's efficiency is quantified by evaluating its performance on the test dataset using the evaluate method. This step calculates the test loss and accuracy, offering a comprehensive assessment of the model's ability to generalize to new, unseen chest X-ray images. To improve the model's performance, a lot of adjustments were implemented to the parameters and hyperparameters.

As previously mentioned, techniques including annealing, learning rate modification, and data augmentation were used to help fit the tiny dataset into the architecture of a deep convolutional neural network. This was done in order to get significant results. The final findings are as follows: validation accuracy is 0.93, validation loss is 0.2119, and training accuracy is 0.97, training loss is 0.0712.

5. Conclusions

We have shown how to categorize a set of X-ray pictures into positive and negative pneumonia data. A deep-CNN-based transfer learning method for the automated diagnosis of pneumonia and its subtypes is presented in this work. Using chest x-ray pictures, four popular CNN-based deep learning algorithms were trained and evaluated for the purpose of differentiating between individuals with pneumonia and those without. VGG16 was found to perform better than the other three deep CNN networks. For the pictures of normal and pneumonia, the corresponding classification accuracy, precision, and recall were 0.93,0.96,0.85 respectively. Every year, this possible fatal condition takes the lives of millions of young people.

REFERENCE:

1. **Efficient Pneumonia Detection in Chest Xray Images Using Deep Transfer Learning -** Mohammad Farukh Hashmi , Satyarth Katiyar , Avinash G Keskar, Neeraj Dhanraj Bokde and Zong Woo Geem - 19 June 2020.
2. **An Efficient Deep Learning Approach to Pneumonia Classification in Healthcare -** Okeke Stephen, Mangal Sain, Uchenna Joseph Maduh, and Do-Un Jeong - 27 Mar 2019.
3. **Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X-ray -** Tawsifur Rahman, Muhammad E. H. Chowdhury , Amith Khandakar - 6 May 2020.
4. **A Novel Transfer Learning Based Approach for Pneumonia Detection in Chest X-ray Images -** Vikash chouhan, Sanjay Kumar Singh, Aditya Khampaira, Deepak Gupta – 12 January 2020.
5. **CXNet-m1: Anomaly Detection on Chest X-rays With Image-Based Deep Learning** – Shuaijing Xu , Hao Wu , Rongfang Bie - 13 December 2018.
6. **Deep neural network ensemble for pneumonia localization from a large-scale chest x-ray database** – Ilyas Sirazitdinov , Maksym Kholiavchenko , Tamerlan Mustafaev , Yuan Yixuan – September 2019.
7. **A survey on deep learning in medical image analysis** – Geert Litjens , Thijs Kooi, Babak Ehteshami Bejnordi – December 2017.
8. **A survey on Image Data Augmentation for Deep Learning –** Connor Shorten and Taghi M. Khoshgoftaar **–** 06 July 2019.
9. **Deep Residual Learning for Image Recognition -** Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun – 2016.
10. **A Survey on Transfer Learning** - Sinno Jailon Pan , Qiang Yang - 16 October 2009.
11. **Deep learning in medical image analysis –** Dinggang Shen , Guorong Wu and Heung-Il Suk – 9 March 2017.
12. **A Web Delivered Locally Computed Chest X-Ray Disease Prediction System** - Joseph Paul Cohen, Paul Bertin, Vincent Frappier - 31 Jan 2019.
13. **Deep Learning for Medical Image Processing: Overview, Challenges and the Future** - Muhammad Imran Razzak, Saeeda Naz and Ahmad Zaib - 14 November 2017.
14. **Deep Convolutional Neural Networks for Chest Diseases Detection** - Rahib H. Abiyev and Mohammad Khaleel Sallam Ma'aitah - 01 Aug 2018.
15. **ImageNet classification with deep convolutional neural networks** - Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton - 24 May 2017.