Classification of Pneumonia on Chest X-Ray Image Using Transfer Learning

Thi Bích Nhu Pham and Minh Hong Nguyen

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Thị Bích Nhu Pham [1] and Minh Hong Nguyen [1]

[1] Can Tho University, 3-2 Street, Can Tho, Vietnam
School of Information Technology - Can Tho University, 3-2 Street, Can Tho City, Vietnam
nhum2522023@gstudent.ctu.edu.com
hongm2522020@gstudent.ctu.edu.com

Abstract. Pneumonia is a dangerous disease and often causes death if not detected and treated promptly. According to the World Health Organization (WHO), every year about 3 million people die from pneumonia worldwide. In this study, we will focus on classifying pneumonia based on traditional machine learning techniques Convolutional Neural Networks (CNNs) with model ResNet50 for the problem of classifying pneumonia through the classification of X-ray images into 3 classes Normal, Bacterial, Viral. We collect X-ray image data from a variety of data sources to build a large and diverse dataset. Evaluation results on a dataset of 2500 X-ray images of the lungs with 710 Normal images, 1080 Bacterial images, 710 Viral images, training and experimental results are the basis for further studies.

Keywords: Classification of pneumonia; X-rays images; ResNet50

1 Introduction

Pneumonia is a dangerous and often fatal disease if not detected and treated promptly. Pneumonia is a disease in which tissues and organs in the lungs become inflamed or infected. Viral pneumonia usually starts off mild and develops gradually, some of the common symptoms of viral pneumonia are: fever, dry or productive cough, shortness of breath, chest pain when breathing, fatigue, pain head, body pain. Bacterial pneumonia usually has more severe symptoms and develops more quickly than viral pneumonia. Some common symptoms of bacterial pneumonia include: high fever, productive cough, severe shortness of breath, chest pain when breathing or coughing. One of the proposed effective solutions to help doctors clinically screen pneumonia cases is to diagnose the disease through screening chest X-ray images.

To reduce the load and better support the doctor when reading X-ray images, especially when working with high intensity and pressure when reading many images for a long time, as well as increasing the accuracy in diagnosis. To diagnose pneumonia caused by viruses or bacteria, building an application that can detect and identify pneumonia diseases is essential for practice.

In this study, we propose an approach in the diagnosis of pneumonia based on chest X-ray images using transfer learning. For example, we do the determination of whether pneumonia is caused by bacteria or by a viral infection.

This study first pre-processed the input images, and then, using a transformation learning model from the ResNet50 deep learning model pre-trained to identify pneumonia diseases. The two models will be tested on the same data set, labeled by experts in the field of cardiology, with very promising results.

This study consists of 5 parts. Part 1 is the introduction and problem definition. Section 2 will present related studies. Part 3 is the implementation method. The next part is the experiments. Finally, conclusions are presented.

2 Related Work

Recently, there have been many related studies in the field of cardiovascular disease identification, in this section, we will summarize some recent studies.

In study [1], the authors proposed using a deep learning approach based on a pre-trained AlexNet model to classify COVID-19, non-COVID-19 viral pneumonia, viral pneumonia. Conventional and bacteriological CXR scans were obtained from various public databases. For non-COVID-19 viral pneumonia and normal (healthy) CXR images, the proposed model achieved an accuracy of 94.43%, a sensitivity of 98.19% and a specificity of 95, 78%. For bacterial pneumonia and normal CXR images, the model achieved 91.43% accuracy, 91.94% sensitivity, and 100% specificity. For COVID-19 pneumonia and normal CXR images, the model achieved 99.16% accuracy, 97.44% sensitivity, and 100% specificity. For CXR images classifying COVID-19 pneumonia and non-COVID-19 viral pneumonia, the model achieved 99.62% accuracy, 90.63% sensitivity, and 99.89% specificity. . . . For the three-dimensional classification, the model achieved an accuracy of 94.00%, a sensitivity of 91.30% and 84.78%. The model achieved 93.42% accuracy, 89.18% sensitivity, and 98.92% specificity for the four-way classifier.

In study [2], the authors proposed training a support vector machine (SVM) model on deep networks such as DenseNet121, MobileNet v2, Inception v3, Xception, ResNet50, VGG16 and VGG19 to detect Covid-19 from chest X-ray images. Classification results for other lung types (opaque lung and pneumonia due to virus) showed that SVM-on-Top achieved the highest classification with cation accuracy of 96.57%.

In study [3], The authors proposed a CNN-based method to distinguish between bacterial and viral pneumonia, stratifying samples and healthy patients.

In this study, we propose to use transfer learning from the pre-trained ResNet50 model and retrain this model on preprocessed data to diagnose and classify pneumonia based on chest X-ray image.

3 Proposed Method

To predict and classify pneumonia, this study will be performed on models ResNet50. Use the trained models on the same data set, then apply the models to predict the same image to see if it is true to the actual results.

3.1 Data Pre-processing

The following applied learning model supporting the diagnosis of pneumonia is trained and tested with modern CNN architectures. The database used in the study uses 2 sets of Covid-19 Image Dataset [4] this dataset has 317 X-ray images and Chest-Xray [5] this dataset has 5856 X-ray images. -The thoracic radiograph was built by Paul Mooney, updated in 2018 and all hosted on Kaggle. In this article, we use 2500 images and 3 types of chest X-ray images extracted from the above 2 datasets, in which 1080 is bacterial pneumonia, 710 viral pneumonia and 710 normal chest . The dataset of the training class is divided into 3 folders including: train, test corresponding to the ratio 80 : 20. Table 1 describes the distribution of images into training the test sets after separation of each image type.

Table 1. Description of the chest X-ray image database

Dataset	Viral	Normal	Bacterial	Total
Full	710	710	1080	2500
Train	560	560	880	2000
Test	150	150	200	500

Figure 1. Normal X-ray image, Viral Pneumonia, Bacterial Pneumonia

In Figure 2, the normal chest X-ray (left image) has a clear lung image without any abnormal opacity in the image. The image of patients with viral pneumonia (middle image) has diffuse “interstitial” in both lungs, whereas bacterial pneumonia (right image) usually presents with focal lobes.

First, the data samples are resized to 224 × 224 pixels and converted to grayscale images, increasing the contrast of the wrong image to clearly show the lung area, processing 900dpi image quality. , each image is then merged into 3 channels resulting in a 224×224×3 input to match the architectures of ResNet50. Then, label all images of the coded dataset once where each class is converted to a binary feature. Doing so helps the machine learning algorithm understand the format of the input and thus perform better. Augmented data is a widely used method in DL that helps to generate the required number of samples. Since our dataset is relatively small, we apply some image enhancement techniques to artificially scale our training data.

To increase the variability in our small database, we applied image extensions by clamping Keras ImageDataGenerator during training, such as random rotation of the image 20˚, zooming large image. randomize the image a range from 0.9 to 1.1, as well as translate the image by height and width proportional to the range from -0.1 to 0.1.

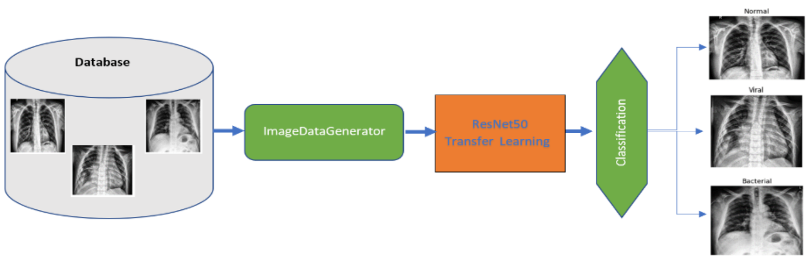

Figure 2. Proposed system workflow for detection and classification in X-ray images

3.2. Architecture ResNet50

ResNet (Residual Network) is a deep neural network architecture introduced by Kaiming He and colleagues in 2015. This algorithm has achieved much success in solving classification problems. image, object recognition, natural language analysis and sound processing.

ResNet uses a fully connected layer to classify images into different classes. After the image has been passed through the convolution and pooling layers, the output is "flattened" to a vector and passed through the full output layer. The full output class uses weights to assign a score to each classification class. The classification class with the highest score will be selected as the final classification result. One of the advantages of ResNet is the ability to learn deep and complex features, which increases the accuracy of the model.

ResNet50 is a version of ResNet network with a total of 50 layers, including 49 convolutional and pooling layers and 1 fully connected layer. The ResNet50 architecture has the same structure as other versions of ResNet, consisting of building blocks with shortcut connections to avoid vanishing gradients.

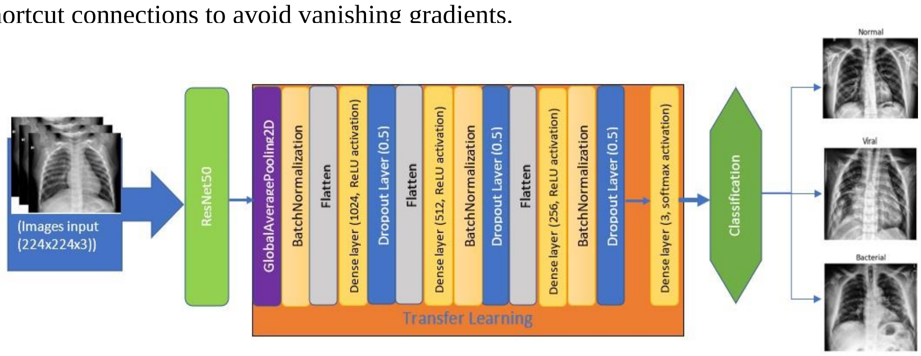

Figure 3: Proposed ResNet50 architecture to classify pneumonia in chest X-ray images

4 Experimental results

The chest X-ray dataset includes three categories: Bacterial Pneumonia, Viral Pneumonia, and Normal. We conducted the experiment with 80% of the total data in the training set and 20% of the validation on the data in the test set. In the case of X-ray imaging of bacterial pneumonia, the ResNet-50 model demonstrated near-perfect accuracy, sensitivity, specificity, F1 score and AUC.

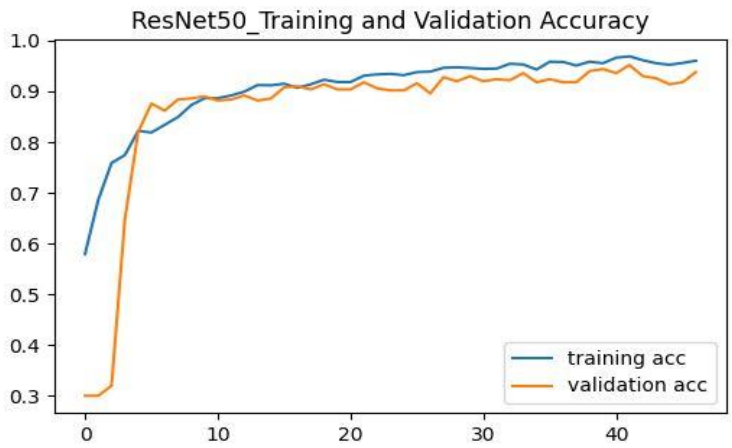

Figure 4. Training and Validation Accuracy of ResNet-50 model

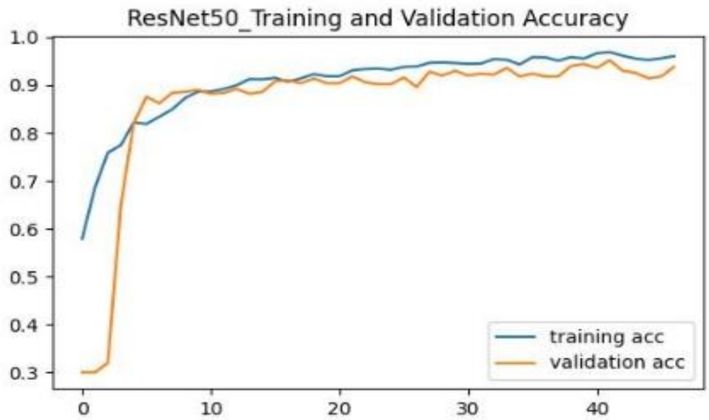

Figure 5. Training and Validation loss of ResNet-50 model

For bacterial pneumonia images, viral pneumonia images and normal images, the ResNet-50 model demonstrated sensitivity values of 0.96, 0.91 and 0.87, respectively. Furthermore, the AUC values suggest that the ResNet-50 model can also identify all 3 groups (Bacterial Pneumonia, Viral Pneumonia and Normal) from chest X-ray with reasonable accuracy (AUC = 92 %). Therefore, the ResNet-50 model can be considered as a reliable method for the detection and classification of bacterial or viral pneumonia.

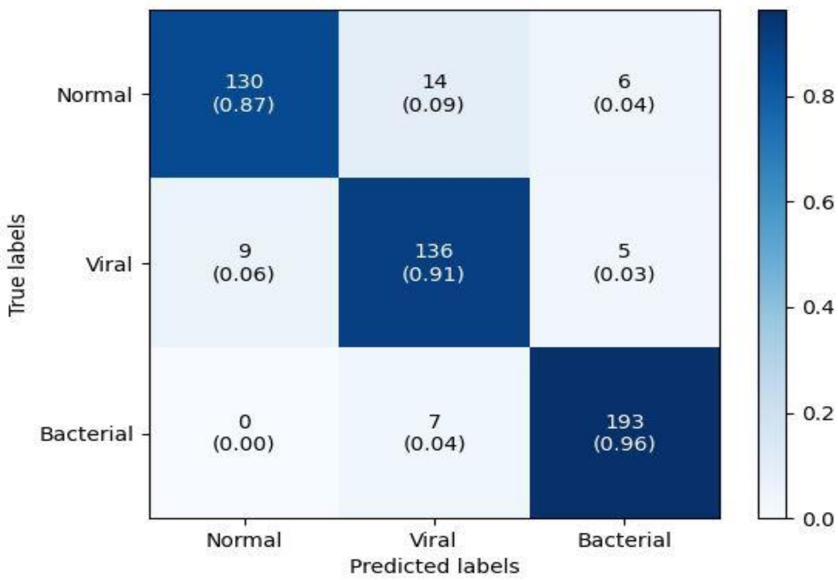

Figure 6. Confusion matrix of ResNet-50 model

5 Conclusion

This work presents the use of deep neural network based on Transfer Learning method to automatically detect and classify bacterial pneumonia images, images Viral pneumonia and common lung imaging. Model was trained on three-dimensional classification (viral pneumonia, bacterial pneumonia, and normal X-ray images), the model was evaluated based on accuracy, sensitivity, and specificity.

Table 2. Description classification report on test dataset

Dataset	precision	recall	f1-score	support
Normal	0.93525	0.86667	0.89965	150
Viral	0.86624	0.90667	0.88599	150
Bacterial	0.94608	0.96500	0.95545	200
accuracy			0.91800	500
macro avg	0.91586	0.91278	0.91370	500
weight avg	0.91888	0.91800	0.91787	500

The results showed that, for the three-dimensional classification (viral pneumonia, bacterial pneumonia and normal) the model achieved test accuracy of 92.00%, specificity of 92.00%. One of the limitations of this study is the fact that we used a larger set of bacterial pneumonia data than the viral pneumonia data and data on bacterial pneumonia. ordinary images. The dataset used for all three classes is not large enough, making generalization of the results difficult. In the future, we hope to get more data sets to train the images and maybe add Grad-CAM application to support disease localization on X-ray images from which to select and apply. The model is suitable to accurately identify the specific disease area on the image.

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