Chest X-Ray Image to Classify Lung diseases in Different Resolution Size using DenseNet-121 Architectures

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ABSTRACT

Chest radiography (CXR) is the most commonly used diagnostic tool in medical practice because of the low cost and easy operation. CXR contains much information about a patient's health, and radiologists often use it for disease detection. The diagnoses are often subjective for a few reasons, like illness looks, which might be unclear in CXR images or are often confused with different diseases. In this study, DenseNet-121 is a well-known convolutional neural network (CNN) model for diagnosing illness. The convolutional layers of these models are used as a base network. The pre-trained model is used because this study applied the transfer learning technique. The pre-trained model is built and trained using the public domain dataset ImageNet.Global Average Pooling (GAP) and dropout layers are added to reduce the overfitting problem of the network. The batch normalization layer is used for the rapid training of the pre-trained model. The output layer consists of 2 nodes that directly represent the two classes and a softmax activation function.This study analyzes the effects of varying image resolution for CXR images using four different datasets: tuberculosis dataset, pneumonia dataset, cardiomegaly dataset, and COVID-19 dataset. It is experimentally shown that DenseNet121 model achieves the highest accuracy in classification using image size 224x224 pixels. The best results were obtained with Tuberculosis dataset, Pneumonia dataset, Cardiomegaly dataset and COVID-19 dataset with 0,892, 0,904, 0,898 and 0,986, respectively.

CCS CONCEPTS

• **Computing methodologies**; • **Artificial intelligence**; • **Computer vision problems**;

KEYWORDS

DenseNet, CNN, CXR, accuracy, chestXRay

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1 INTRODUCTION

Chest X-ray (CXR) is the one most frequently used for diagnostic purposes. CXR is the most commonly used to detect illnesses, such as tuberculosis, pneumonia, and cardiomegaly. CXR is a very affordable and relatively safe method for investigating chest diseases. However, classifying and detecting diseases from CXR needs professional radiologists, a rare and expensive resource for some regions [1]. The complexity of reading CXR images makes computer-aided detection (CAD) systems a popular research topic since the system can help radiologists improve their detection and classification accuracy.

Recently, Convolutional Neural Network (CNN) has received a lot of attention in computer vision to solve various visual tasks in medical imaging fields [2]. CNN can be applied to enhance the performance of CAD systems. CNN has demonstrated superior results in medical images classification and detection tasks, which are detecting diabetic retinopathy in retinal images [3], classifying dental diseases [4], classifying face skin disease [5], detecting breast cancer [6], brain tumor segmentation [7], and detecting alzheimer disease [8]. Therefore, the CNN method that automatically learns image features to detect and classify diseases has become a mainstream trend.

Many research articles have been published related to using CNN methods to classify diseases using CXR images. Various studies have explored the applicability of analyzing such CXR datasets using the CNN method to help with radiological imaging diagnosis. Wang et al. published a survey on eight disease classification in CXR imaging using four different models: AlexNet, GoogLeNet, VGGNet-16, and ResNet-50 [9]. Rajpurkar et al. experimented with 121-layer CNN and approached treating the uncertainty in the manual labels to classify pneumonia in their chest X-ray dataset [10]. Taylor et al. used CNN to detect pneumothorax using the National Institutes of Health (NIH) ChestXray14 dataset [11].

DenseNet-121 can be seen as an architecture that takes the insights of the dense connection, connecting each layer to every prior layer to improve the information flow between layers [12]. Recently, several studies have been carried out to classify medical images using DenseNet-121. Pardede et al. [13] reported 94% accuracy for Melanoma Skin Cancer detection from skin lesion image. Rajpurkar et al. [10] and Irvin et al. [14] used DenseNet121 model to classify 14 disease classes with large dataset. Khan et al. [15] used dataset consists of 27,558 cell images for malaria parasite detection and reached a classification accuracy of 96.6%. Solano-Rojas

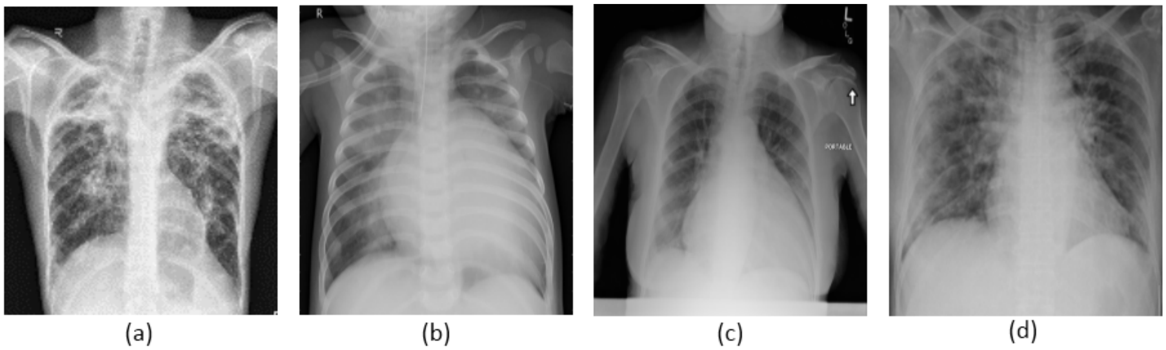

Figure 1: sample xray images

et al. [16] reported accuracy, specificity and sensitivity of 87%, 87% and 88%, respectively using the Magnetic Resonance Imaging (MRI) dataset for Alzheimer's Disease early detection. It was observed that DenseNet-121 architecture can help to solve various medical image classification tasks with high accuracy. Therefore, this study uses DenseNet-121 model and transfer learning technique to classify four datasets, each with two classes.

The study's objective is to acquire and compare various data sizes, which is essential for classification. Each classification result is compared to get the best performance from the seven image sizes tested using DenseNet-121.

2 DATASET

This study uses four different datasets. Chest X-ray (CXR) images are used to find out the performance of CNN model to classify disease. Each image in the datasets is labeled according to its classes. The three publicly available datasets in the experiment are:

1. Tuberculosis dataset [17]: The set consists of 662 frontal CXR images in PNG format. This dataset is collected from Shenzhen No.3 People's Hospital, Guangdong Medical College, Shenzhen, China, divided into 326 normal and 336 tuberculosis. All X-ray images have an approximate size of 3K × 3K pixels. Figure 1(a) shows images of the Tuberculosis dataset.
2. Pneumonia dataset [18]: This set contains 5856 frontal CXR images. The images are varying sizes, such as 712x439 pixels to 2338x2025 pixels. Figure 1(b) shows images of the Pneumonia case. The set is classified into two categories: normal and pneumonia. The set contains 3616 CXR images, among which 1093 are pneumonia cases and 3620 are normal cases.
3. Cardiomegaly dataset [9]: This set is collected from ChestX-ray8 and is directly extracted from the DICOM file. The set contains 2186 CXR images, among which 1093 are cardiomegaly cases, and 1093 are normal cases. Figure 1(c) shows images of the Cardiomegaly dataset.
4. COVID-19 dataset [19,20]: This dataset was obtained from COVID-19 Radiography Database (Winner of the COVID-19 Dataset Award by Kaggle Community). The set contains 7236 CXR images, among which 3616 are COVID-19 cases, and 3620 are normal cases. Figure 1(d) shows images of COVID-19 dataset.

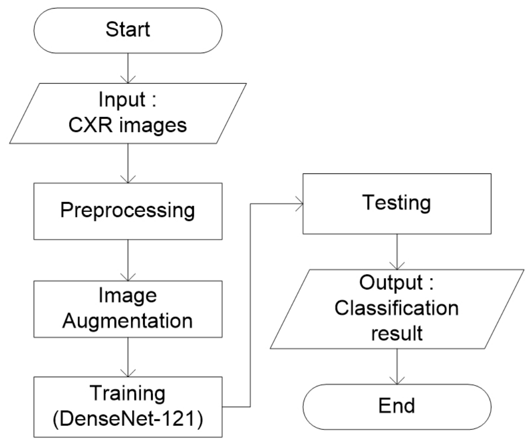

Figure 2: Flowchart for disease classification

3 METHODOLOGY

In the present study, the classification process is divided into four tasks: preprocessing, image augmentation, training, and testing. The methodology adopted for disease classification has been explained in Figure 2.

3.1 Preprocessing

For generating varying resolution sets of the original image, an image rescale/resize operation is performed on an original image without loosing any image information. The resolution sizes that be used in this experiment are 32x32 pixels, 64x64 pixels, 100x100 pixels, 128x128 pixels, 150x150 pixels, 175x175 pixels, 200x200 pixels and 224x224 pixels.

The dataset is split into training, validation, and test sets. The training set is used for fitting the model, while the validation set aims to avoid overfitting problems. A validation set is required to act as an indicator of the generalizability performance of the model to new and unseen data [21]. The training sets are randomly divided into 80% for training and while the test set has 20% images in the dataset. The performances of the models are evaluated on the test set.

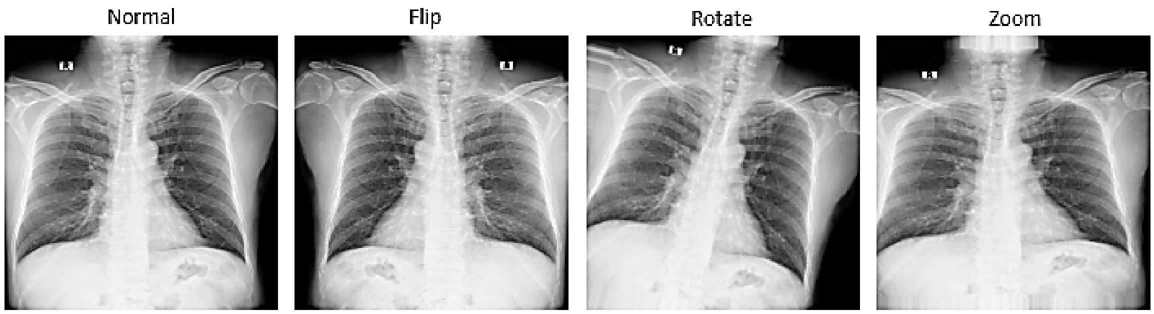

Figure 3: Data augmentation result.

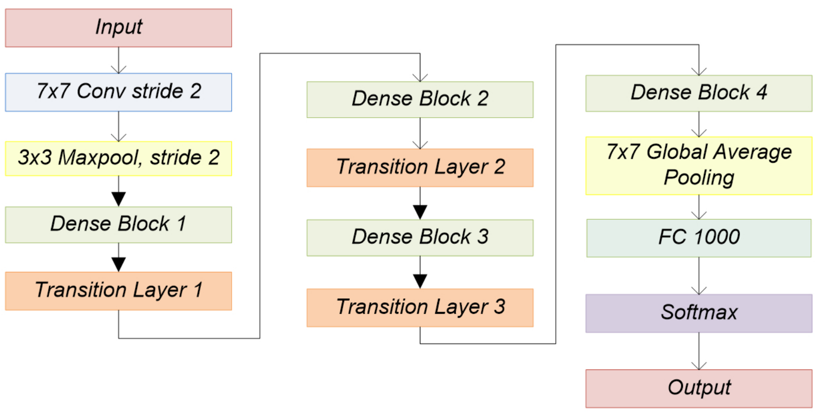

Figure 4: Original Architectures of DenseNet-121.

3.2 Image Augmentation

Convolutional neural networks are better adjusted using a large amount of training data. However, medical image datasets square measure arduous to gather as a result of it desires plenty of skilled experience to label them. Due to the lesser samples in the training data set, data augmentation is performed to ensure model generalizability and prevent model overfitting. The augmentation technique is implemented to increase the number of training images. Generated images in the studies are mainly used for data augmentation to have a more balanced dataset for training neural networks of classification or segmentation. With the synthetic images, classification or segmentation accuracies are significantly increases than those with the imbalanced dataset. This study applied some transformation to the original training image to generate artificially new training images such as horizontal flip, zoom, rotate, and shifts. Images in Figure 3 shows some of the images generated by using data augmentation.

3.3 Convolutional Neural Network

Convolutional neural networks (CNN) are the most popular machine learning methods, especially data that have a known-like topology like the human visual cortex [22]. Compared to other machine learning methods, the advantage of CNN is its ability to extract features automatically without human intervention [23]. CNN's ability is very dependent on the architecture that is built [24]. Basic CNN has three components: convolutional layer, pooling layer, and fully connected layer.

Densely Connected Convolutional Networks (DenseNet) is one of the CNN architectures introduced by Huang et al. [11]. DenseNet is built from dense blocks and transition layers. Each layer is directly connected to every layer in front of it [25]. A dense block contains three operations (Batch normalization, ReLU, and Conv). Conv and average pooling are used as the transition layers between two contiguous dense blocks. Concatenation is utilized, and each layer receives feature maps from all preceding layers so that network can be thinner and compact. For guaranteeing that the feature maps are connected, the feature map size is required to be steady, indicating that the size of the convolution layer of the input and output is the same [26]. DenseNet-121 has 121 layers consisting of 116 convolution layers divided into four dense blocks, four pooling layers, three transition layers, and one classification layer. Figure 4 shows original architectures of DenseNet-121 [12].

The proposed model that is used in the training process is illustrated in Figure 5. This study used the pre-trained DenseNet-121 model, where the fully connected layer of the original DenseNet-121 model is removed. The convolutional layers of these models are used as a base network. The pre-trained model is used because this study applied the transfer learning technique. The pre-trained model is built and trained using the public domain dataset ImageNet.Global Average Pooling (GAP) and dropout layers are added

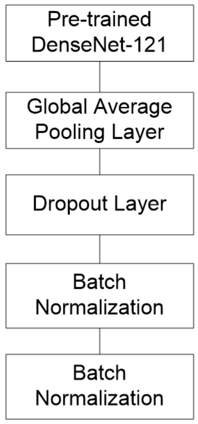

Figure 5: Architecture of proposed model

to reduce the overfitting problem of the network. The batch normalization layer is used for the rapid training of the pre-trained model. The output layer consists of 2 nodes that directly represent the two classes and a softmax activation function.

3.4 Training

The training set was randomly divided into two subsets: 80% of training sets for the augmentation process and 20% training sets for the validation process. CNN has been trained with Adam optimizer, which is known to be fast and effective for computer vision related problems. In this work, the transfer learning and fine tuning technique is used with a pre-trained DenseNet-121 model. The architecture CNN model can be seen in Figure 4. The training set generated from the augmentation process will replace the original training data for use in the training process.

3.5 Testing and Evaluation

For the performance evaluation of CNN-based image classifier, standard classification performance metrics accuracy is used in this experimental methodology. The confusion matrix is one of the most intuitive and easy metrics used to find the accuracy of any model. This experiment uses a confusion matrix based performance measure score. There are four outcomes of binary classification:

- TP be true positives (data labeled as positive that are positive).
- FN be false negatives (data labeled as negative that are positive).
- FP be false positives (data labeled as positive that are negative).
- TN be true negatives (data labeled as negative that are negative).

The relationship between these prediction outcomes can then be summarized using a confusion matrix (Kohavi et al. 1998). This study evaluates the performance of the DenseNet-121 in terms of accuracy. The formula for performance measure scores is given in Equations (1).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

4 RESULT

The processing was performed using a PC with the following configuration: Intel Xeon CPU E3-1220 v3 @3.10 and 16.00 GB RAM. The proposed method was implemented in Python language by using Jupiter Notebook. Keras and TensorFlow frameworks were the development environments. For each experiment, the learning rate was set to 0.0001, total epochs were 10, and batch size was 16.

In this experiment, the manipulated variables would be the image size of train networks. All images are downsized to some different size such as 32x32, 64x64, 100x100, 128x128, 150x150, 175x175, 200x200, and 224x224. To improve classification performance, prevent overfitting, and enhance the robustness of the network, a data augmentation method was used for the training dataset. The augmentation process used Image Data Generator that Keras provided. Augmented image data were created just in time. This process can reduce memory overhead but added some additional time cost during model training. Some transformations such as horizontal flipping, zooming (0.1), shifting (0.05), and rotating (20) were applied to the original training image to generate artificially new training images. It can be seen that for more significant image size accuracy score performed better than a small image sizes accuracy score.

Confusion matrix is used to get a better understanding of the results. The results in the confusion matrix were used to calculate accuracy value for each dataset. As shown in Table 1, the highest accuracy of 0.892 on the Tuberculosis dataset, 0.923 on the Pneumonia dataset, 0.897 on the Cardiomegaly dataset, and 0.986 on COVID-19 dataset are achieved with big image size. The accuracy has shown that the smallest image size always has the lowest accuracy on the experiment results. It is proven that the smaller value of image sizes has the lowest accuracy on classification. In tuberculosis and cardiomegaly datasets, image sizes smaller than 100x100 pixels showed indicators of network poor generalization performance. Based on Table 1, the size of training data with the best results is 224x224 pixels.

5 CONCLUSION

The use of chest X-ray (CXR) images for the detection of diseases is a promising technique. The experiment used four different datasets: tuberculosis dataset, pneumonia dataset, cardiomegaly dataset, and COVID-19 dataset. In this work, popular Convolutional Neural Network architectures were applied to classify diseases based on CXR images into two classes: without diseases (normal) and with diseases.

Architectures used DenseNet-121 with the pre-trained model that Keras provided. According to the experimental results, every image size could generate different results on all datasets. Image size with 224x224 pixels successfully classifying tuberculosis, pneumonia, cardiomegaly, and COVID-19 cases with the best performance. In future work, other CNN models are proposed, such as Xception and MobileNet. It may be interesting to see the effect of architecture CNN models in a future study to increase the speed and accuracy on diagnosing diseases from chest X-ray images.

Table 1: Accuracy result for all dataset.

Image Size	Tuberculosis	Pneumonia	Cardiomegaly	COVID-19
32x32	0.705	0.862	0.779	0.903
64x64	0.837	0.914	0.834	0.942
100x100	0.855	0.904	0.834	0.960
128x128	0.849	0.908	0.870	0.973
150x150	0.862	0.910	0.882	0.979
200x200	0.886	**0.923**	**0.898**	0.973
224x224	**0.892**	0.904	**0.898**	**0.986**

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