ISSN 2278-3091
Volume 9, No.4, July – August 2020
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse301942020.pdf
https://doi.org/10.30534/ijatcse/2020/301942020

Identification of Normal and Diseased Lungs using X-ray Images through Transfer Learning

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ABSTRACT

Due to the emerging technology, it is starting to get smarter as time proceeds into the future. Various of uses and application are available including in the medical field. Artificial Intelligence is one of the most useful application of technology in today's society, a machine that you can train through feeding of various information. Its importance in the medical field sought to find its way creating a faster and more efficient examination. There are 1000 images composed of different x-ray images classified as normal or with respiratory diseases such as cardiomegaly, atelectasis, effusion, infiltration, fibrosis, and pneumonia. This study used transfer learning to classify x-ray images using pre-trained weights from different convolutional neural network models (CNN) such as DenseNet121, ResNet50, InceptionV3, VGG16, and VGG19. DenseNet121 and InceptionV3 model attained the highest accuracy, 100% and the VGG19 model registered the lowest accuracy, 78.38%.

Key words : convolutional neural network, respiratory diseases, transfer learning, X-ray

1. INTRODUCTION

The chest X-ray is a normally available radiological examination which screens and diagnoses lung diseases [1]. People are most likely to get respiratory conditions and diseases due to unhealthy lifestyle. The workplace or environmental exposure could also play a big role in one's health.

The lungs play a vital role in the body such as delivering of oxygen to the blood and even removing particles from the airways. Indeed, it is one of the most important part of the body, however it is also the most abused. According to the American Lung Association, smoking, nicotine addiction, air pollution, obesity and even climate change can affect the health of our lungs in a certain level [2].

As the researchers gives important to everyone's health, the researchers formulated a program that can detect a certain respiratory problem through x-ray images.

The research was made possible by gathering various images and running it into a machine learning application, Python to be exact thus creating an AI that can detect the respiratory diseases. The formulated study can help the medical field in making a faster and efficient interpretation of the x-ray result thus saving more time and catering more patients.

The researchers propose to visually understand the respiratory diseases by gathering images of x-ray obtained from reliable and free access websites and classify each image into chest x-ray category via machine learning. Machine learning covers many powerful tools with the possibility to intensely sustains the information by the radiologists from the extracted images.

This study only involves respiratory diseases such as atelectasis, cardiomegaly, plural effusion, pulmonary fibrosis, pulmonary infiltrate, and pneumonia.

2. METHODOLOGY

2.1 Transfer Learning

Transfer learning is a prevalent deep learning method where models which were pre-trained are utilized as the initial point on jobs related to computer vision (CV) and natural language processing (NLP). Immense computing and period resources are needed to develop the said models to solve these difficulties [3],[4],[5].

2.2 Keras Platform

This is a high-level API for neural networks, coded using Python and able of executing with programs such as TensorFlow, CNTK, or Theano. It was developed with an emphasis on allowing fast experimentation. If there is a need in deep learning which tolerates less difficult and more quick prototyping, aids convolutional networks, and executes faultlessly on CPU and GPU, one must use Keras. It is compatible with Python 2.7-3.6 [3],[6].

2.3 Dense Net121

This model simplifies the "connectivity pattern between layers" presented in different systems such as Highway Networks, Residual Networks, and Fractal Networks. One of problems in deep neural networks was training due to the said information and gradients flow. To solve this problem, DenseNet is developed so that each layer has "direct access to the gradients from the loss function and the original input image" [7],[8].

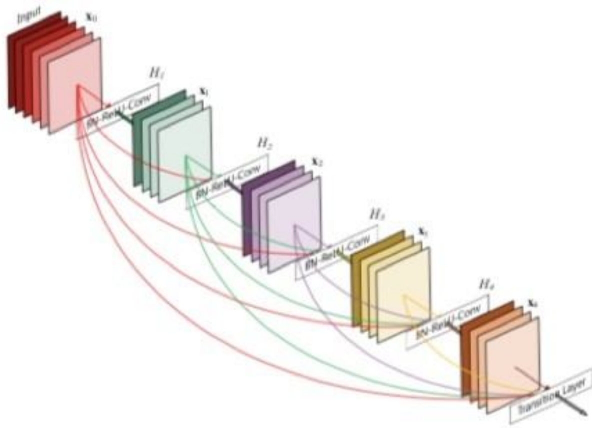

Figure 1: DenseNet with 5 layers with expansion of 4 [8]

2.4 InceptionV3

InceptionV3 is a CNN "that is trained on more than a million images from the ImageNet database" [9]. It has 48 layers in depth. In InceptionV3, images are classified to one thousand (1000) object categories. 299x299 is the image input size of InceptionV3.

2.5 ResNet50

This is a deep residual network. "50" refers to the number of layers it has. It is a subclass of CNNs, with ResNet as the most popularly used for image classification. Without adjustments, deep networks often suffer from vanishing gradients. Tiny gradients can make learning defiant. That's why the "skip connection", which is the main innovation of ResNet, was used. It allows the network to learn the identity function [10].

2.6 VGG16

It is a CNN model which attains 92.7% top-5 test accuracy in ImageNet. ImageNet contains more than 14 million images of datasets which belongs to 1000 classes [11].

2.7 VGG19

VGG19 is specifically trained on over a million images from the "ImageNet" database. If we will compare the VGG16 and VGG19, their main difference is that VGG19 consists of 19 layers of deep neural network whereas VGG16 consists of 16 layers of deep neural network respectively. They also differ in terms of size wherein VGG16's size is 533 MB while VGG19's size is 574 MB respectively. This is in terms of fully connected nodes [11].

2.8 Dataset

The images needed for the development of the project are collected from www.kaggle.com. Figure 2 shows sample of images of x-ray classified as normal and respiratory diseases

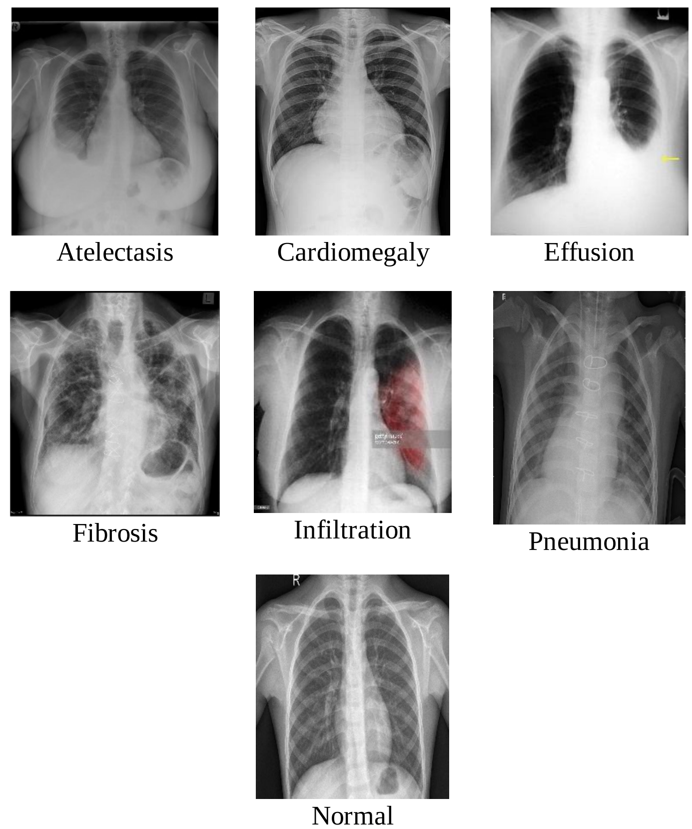

Figure 2: Sample Images of Dataset

The datasets came from free access reliable website. It is composed of 2 categories of chest x-ray and each image is in .jpeg extension. There is a total of 1000 images breaking down as follows in Table 1:

Table 1: Dataset

Category	Number of Images	Train Data	Test Data	Validation Data
Normal	300	250	50	50
Respiratory Diseases	700	583	117	117
Total	1000	833	167	167

The dataset is divided to 83% for training and 17% for testing. The validation data is collected from either the train data or the test data also. As shown in Table 1, train data composed of 833 images while the test data composed of 167 images the same with the number of validation data.

2.9 Experiment

The program will be implemented using PyCharm IDE. Keras platform will be used with TensorFlow backend in coding the system. The system can detect the different x-ray images of a normal lung and a lung with a disease. This is done by using transfer learning models of convolutional neural network, such as DenseNet121, ResNet50, InceptionV3, VGG16 and VGG19.

The program starts at organizing imports such as NumPy, Keras, scikit-learn and matplotlib. It will then split the training and testing data by configuring the dataset into specific directories (training, testing and validation). Then, it is to load the x-ray images of a normal and a diseased lung from the subfolders of the categories. Next, it will create a base model of different pretrained convolutional neural networks. It will then acquire the features by preprocessing the data. Keras will take care of this automatically with its utilities [12],[13]. Then, it will configure the training and testing of the model. Adam optimizer is used in training the model. Lastly, after the training is finish different architectures will be evaluated and compared base on model accuracy, confusion matrix, loading time, and weight size to verify what is the best architecture for the Respiratory Diseases classification.

Using pretrained convolutional networks size of the input image varies for every model. The input image equals the image size (width and height) and the quantity of channels. Table 2 presents the fixed size of the input image of every model that was used.

Table 2: Input for every model

Model	Input Image
DenseNet121	224x224x3
ResNet50	224x224x3
InceptionV3	299x299x3
VGG16	224x224x3
VGG19	224x224x3

3. RESULTS AND DISCUSSIONS

To compare and verify the effectiveness of each pre-trained convolutional neural networks in respiratory disease classification following criteria was observed:

3.1 F1 score

Fig 3 shows the F1 score which measures the accuracy of the test.

	precision	recall	f1-score	support
Normal	0.26	1.00	0.41	40
Respiratory Diseases	0.00	0.00	0.00	113
accuracy			0.26	153
macro avg	0.13	0.50	0.21	153
weighted avg	0.07	0.26	0.11	153

Figure 3: F1 score

3.2 Confusion Matrices

Figures 4 to 8 show the confusion matrices of different models.

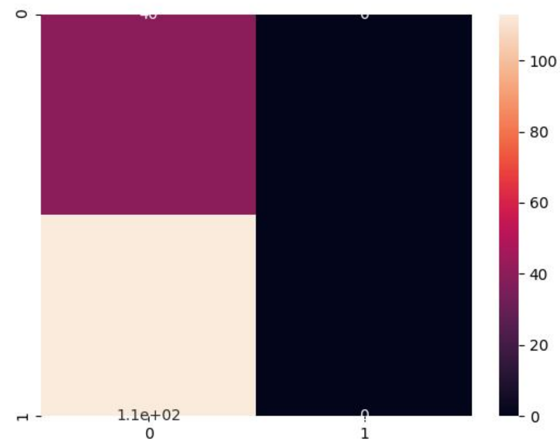

Figure 4: DenseNet 121 Confusion Matrix

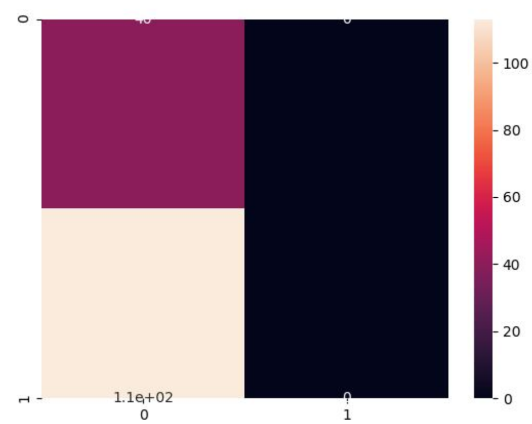

Figure 5: ResNet50 Confusion Matrix

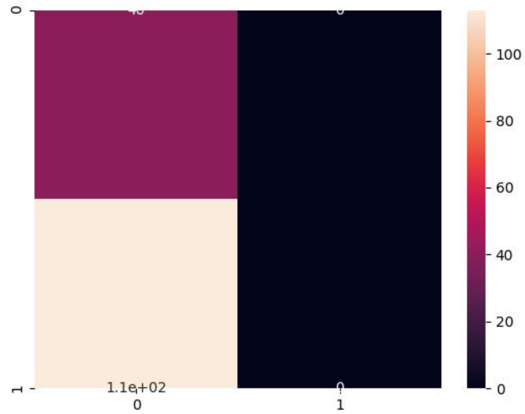

Figure 6: Inception V3 Confusion Matrix

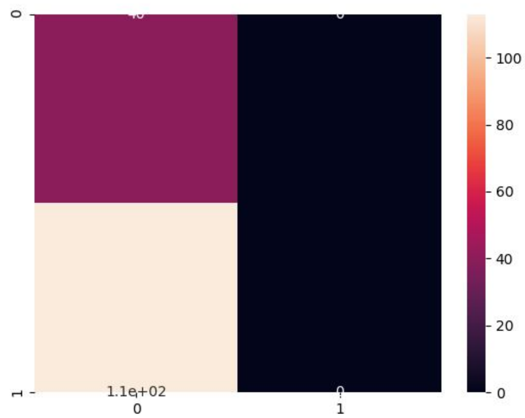

Figure 7: VGG16 Confusion Matrix

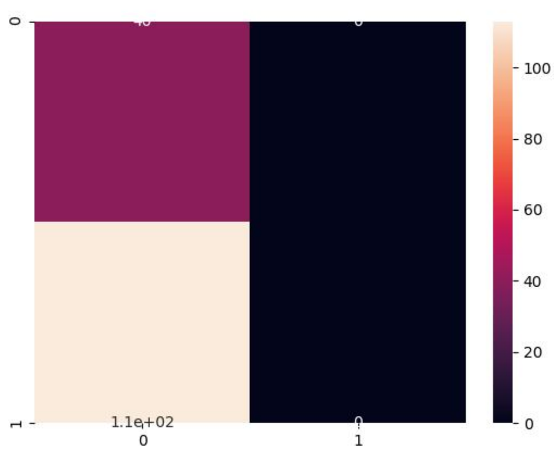

Figure 8: VGG19 Confusion Matrix

3.3 Weight Size, Loading time and Accuracy

The highest performing model is the DenseNet121 and InceptionV3 with an accuracy of 100% and a weight size of 33.317MB and 93.860MB which has the highest accuracy and least size in terms of weights among the models.

Table 3: Evaluation of each Models by its Weight size, Loading time and Accuracy

Model	Weight Size	Loading time (in minutes)	Accuracy (Percent)
DenseNet121	33.317MB	18	100
ResNet50	100.443MB	17	93.92
InceptionV3	93.860MB	8	100
VGG16	540.496MB	20	93.92
VGG19	561.242MB	20	78.38

4. CONCLUSION

This study used transfer learning in classification of respiratory diseases. It could be easy to classify an image of x-ray whether it is normal or with respiratory diseases like atelectasis, cardiomegaly, effusion, fibrosis, infiltration, and pneumonia just by identifying every pixel in the picture which could be difficult to detect by the naked eye. Pretrained models were used such as VGG16, VGG19, ResNet50, InceptionV3, and DenseNet121. The results show that DenseNet121 and InceptionV3 are the highest performing models with an accuracy of 100%. Also, they are also the one with least size in terms of weights among the models having a weight size of 33.317 MB and 93.860 MB.

ACKNOWLEDGEMENTS

The authors would like to express their gratitude to the University Research and Development Services Office of the Technological University of the Philippines for the funding.

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