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Model development for pneumonia detection from chest radiograph using transfer learning

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ABSTRACT

Accurate interpretation of chest radiographs outcome in epidemiological studies facilitates the process of correctly identifying chest-related or respiratory diseases. Despite the fact that radiological results have been used in the past and is being continuously used for diagnosis of pneumonia and other respiratory diseases, there abounds much variability in the interpretation of chest radiographs. This variability often leads to wrong diagnosis due to the fact that chest diseases often have common symptoms. Moreover, there is no single reliable test that can identify the symptoms of pneumonia. Therefore, this paper presents a standardized approach using convolutional neural network (CNN) and transfer learning technique for identifying pneumonia from chest radiographs that ensure accurate diagnosis and assist physicians in making precise prescriptions for the treatment of pneumonia. A training set consisting of 5,232 optical coherence tomography and chest X-ray images dataset from Mendelev public database was used for this research and the performance evaluation of the model developed on the test set yielded 88.14% accuracy, 90% precision, 85% recall and F1 score of 0.87.

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1. INTRODUCTION

Pneumonia, a pulmonary disease, in which air sacs in the lungs, also referred to as alveoli, are filled up with fluid such as pus [1]. It is a pulmonary infection occasioned by virus or bacteria, resulting in the death of approximately 1.4 million children yearly. By implication, this statistic indicates that about 18% of children born die at less than five years of age. Globally, nearly 156 million children are currently suffering from the attack of pneumonia [2]. Findings revealed a great burden of communicable diseases in the world in which about 30% of world childhood deaths are caused by acute respiratory infection [3]. Unlike other parts of the human body, the difficulty associated with accessing the chest region makes the diagnosis of common chest ailments very challenging to medical practitioners [4], [5]. To reduce the mortality rate caused by chest region diseases such as pneumonia, the World Health Organization (WHO) established a child health epidemiology grouped (CHERG) in the year 2001. CHERG was saddled with the responsibility of carrying out a systematic review and data collection improvement, methods, and assumptions, underlying the estimates of death's causes distribution in children for year 2000 [6].

2. REVIEW OF LITERATURE

Chest radiograph, also known as chest X-ray (CXR), is among periodically performed radiological procedures that use little dose of ionizing radiation to capture images of the interior of human chest, lungs, and heart [7]. It is useful in diagnosing, monitoring, and treating diverse lung conditions such as cancer, pneumonia, and tuberculosis [8]. Radiological result has been a major means of diagnosing pneumonia but the major problem with the approach is the lack of uniformity in chest radiograph's interpretation [9], [10] and hence a standard approach is required since there is no single reliable test that can identify the symptoms of pneumonia. Medical imaging means techniques and procedures used in creating images of human body parts such as radiography, Magnetic resonance imaging, ultrasound, and endoscopy [11]. Computers can be leveraged in the analyzing medical images to gain a better understanding and interpretation of medical images [12], by leveraging the hierarchical feature representation learned from data instead of the common hand-made features that are mostly designed based on domain-specific knowledge [13]. Deep learning incorporates feature engineering into the learning step in its learning analysis [14], and therefore requires only a dataset with little pre-processing where informative representations are discovered in a self-learning manner [15], [16]. One of the popular recent applications is AlphaGo and AlphaZero, developed by DeepMind [17]. Deep learning is also used in object detection to detect the position of an object in image. This application is useful to detect early symptoms of abnormality present in patients. Furthermore, it is used in image segmentation for finding anatomical structures that are present in an image.

Deep learning has received significant attention due to its ability to process a huge number features when dealing with unstructured data as could be found in [18], [19]. It was implemented in [20], [21] for the detection and localization of abnormalities in chest radiographs with huge success. At the center of deep learning is artificial neural networks (ANNs) models manually extract features from raw data or features learned by other simple models. This enables systems to authomatically learn useful representation and features from raw data, without the tedious manual procedure. Its choice in medical image analysis is mostly triggered by convolutional neural networks (CNNs) [22]-[24], which is good at learning useful representation of image data, and other data structured. To sufficiently use CNNs, features has to be typically designed by hand, and can identify features that are relevant in a dataset without human interaction [25], [26] which make it practicable to utilize features learned directly from data [27], [28]. While ANN need much data to learn the patterns and associations in data, deep learning does not. The diagnosis of diseases of the chest using radiographs have aroused research interests and has been deployed for the diagnosis of lung nodule [29] and the classification of lung tuberculosis [30]. Using open datasets, many convolutional models are based on several abnormal features [31] which revealed that the same CNN does not replicate performance on every abnormal feature. Accuracy is improved when the comparison is made between deep learning techniques and rule based techniques. Dependency based on statistics between labels was implemented to get better and accurate predictions, resulting in better performance than other methods implemented on 13 images that were selected out of 14 classes [32]. Mining algorithms and labels prediction arose from radiographs including their report have been researched [33]-[35], the labels of the radiographs were all limited to radiographs that have disease labels which resulted in a lack of contextual facts. Radiography detection of diseases was studied in [36]-[38], and reported categorization based on image views from radiographs was reported in [39] while isolation of body parts from chest radiographs plus computed tomography was implemented in [40]. Inception v3 is a known model that can be leveraged to achieve very high accuracy in image recognition [41] as applied in Bar *et al.* [42] with encouraging results and used in this paper because it requires few computing resources.

3. METHOD

The data used in this paper was obtained from optical coherence tomography, and X-ray images of chest from the Mendeley public database [43]. As presented in Figure 1, the training set used is 5,232 images out of 5856 chest X-ray images collected from children. Out of these, 3883 X-ray images belong to patients/children diagnosed with pneumonia while 1349 X-ray images belong to children that are free from pneumonia. The validation set were 16 images while the test set were 624 images. Labels were given to the images as it is done in supervised learning. A model was created using Inception-V3 transfer learning on Tensorflow, which was trained using 5232 images out of which 3883 were from pneumonia children and 1349 were from normal children. The trained model was tested with 624 images out of which 390 contains pneumonia and 234 were from normal children.

The research design consists of steps implemented on Inception-v3 CNN as indicated in Figure 2. The first stage constitutes the system architecture. In the second stage, the images are read into the system, while the third stage involves pre-processing the input image. The input image was irregular in size and cannot pass through the learning algorithm, which expects the input images to be of size 224×224. Using bilinear interpolation, the images were resized to the required dimension. The images were represented as array of pixel values ranging from intensity level 0 to 255. In order to ensure that the data is suitable for learning, the pixels were scaled down by (1).

$$P' = \frac{p}{255} \tag{1}$$

Where p is the original value of pixel, and P' the new value of pixel within the range 0 to 1. The pre-processing tasks include image resize to ensure uniform dimension for the images. The images were then scaled to within range 0 to 1 for each pixel. A data generator object was used to deliver the images in batches of 64 images each. The next step is training the system before finally generating the model.

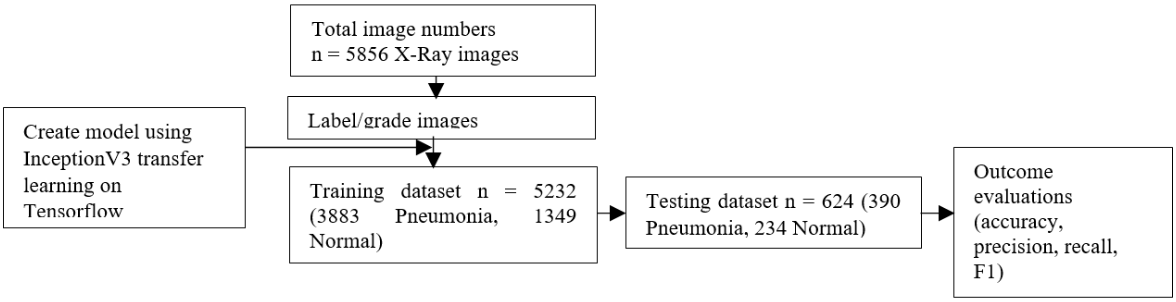

Figure 1. Workflow diagram

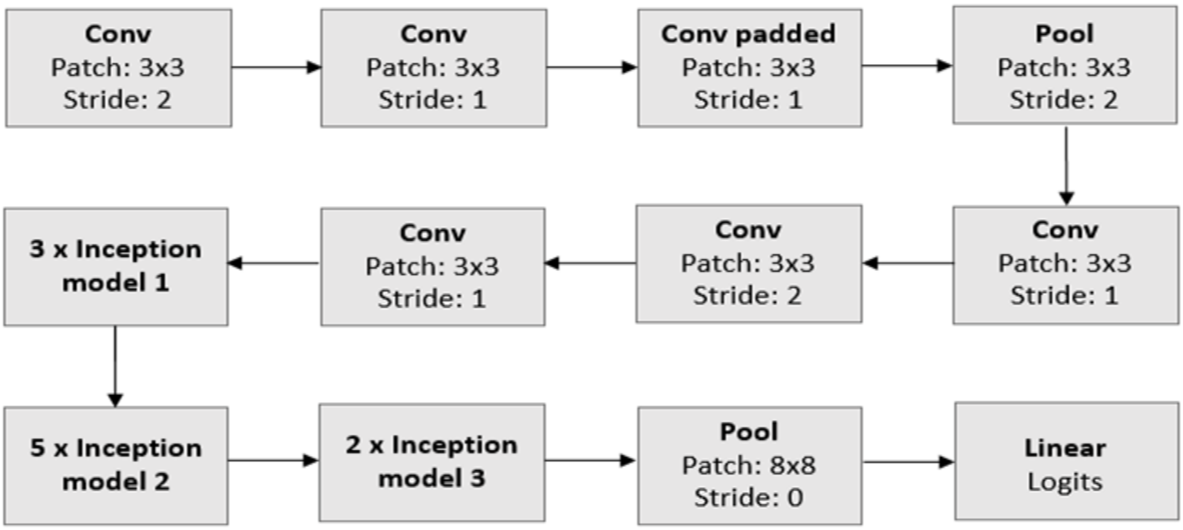

Figure 2. The basic architecture of Inception-V3

4. TRAINING THE NETWORK

Transfer learning was carried out from a pre-trained base model (Inception-V3). It is a publicly available model trained on the ImageNet database of 14 million annotated images classified into 1000 categories of objects. It is a deep CNN architecture that was trained for detection and classification based on the imagenet large-scale visual recognition challenge 2014 (ILSVRC14). The network's architecture was specially designed to optimally utilized the computing resources. The network has 27 layers deep including 5 max pooling layers as shown in Table 1. In order to adapt this architecture to the objective of diagnosing pneumonia from X-ray images, a global average pooling layer and a new dense layer were added to the end of the network. A new two class output layer replaced the softmax 1000-class output layer.

Table 1. Layers of the network

Type	Patch size	Output size	Depth	#1×1	#3×3	#5×5	Pool proj.
Convolution	7×7/2	112×112×64	1				
Max pool	3×3/2	56×56×64	0				
Convolution	3×3/1	56×56×192	2		192		
Max pool	3×3/2	28×28×192	0				
Inception(3a)		28×28×256	2	64	128	32	32
Inception(3b)		28×28×480	2	128	192	96	64
Max pool	3×3/2	14×14×480	0				
Inception(4a)		14×14×512	2	192	208	48	64
Inception(4b)		14×14×512	2	160	224	64	64
Inception(4c)		14×14×512	2	128	256	64	64
Inception(4d)		14×14×528	2	112	288	64	64
Inception(4e)		14×14×832	2	256	320	128	128
Max pool	3×3/2	7×7×832	0				
Inception(5a)		7×7×832	2	256	320	128	128
Inception(5b)		7×7×1024	2	384	384	128	128
Avg pool	7×7/1	1×1×1024	0				
Dropout (40%)		1×1×1024	0				
Linear		1×1×1000	1				
Softmax		1×1×1000	0				

5. MODEL EVALUATION METRICS

The performance was based of the following metrics:

- Classification accuracy: this is the ratio of the correctly classified images to the total number of image samples, presented in (2).

$$\frac{CCI}{TNI} \times 100 \tag{2}$$

Where, CCI = correctly classified images and TNI = total number of images.

- Precision: this is the number of images correctly classified as having pneumonia against the number of images classified as having pneumonia multiplied by wrongly classified as having pneumonia. This is presented in (3).

$$\frac{CDP}{CDP \times WDP} \tag{3}$$

Where, CDP = correctly diagnosed pneumonia and WDP = wrongly diagnosed pneumonia.

- Recall (sensitivity): this is the ratio of number of images correctly classified as having pneumonia to the total number of images that actually have pneumonia multiplied by number of images wrongly classified as having pneumonia. This is presented in (4).

$$\frac{CDP}{CDP \times WDAP} \tag{4}$$

Where, CDP = correctly diagnosed pneumonia and WDAP = wrongly diagnosed as pneumonia.

- F1 score: it is the weighted average of recall and precision. This measure shows the balance between precision and recall. This is presented in (5).

$$\frac{2 \times precision \times recall}{2 + precision + recall} \tag{5}$$

6. RESULT AND DISCUSSION

The implementation of this work was done in python programming language in a python notebook environment. Training was done in the 'train.py' script, evaluation and generation of reports in the 'evaluate.py' script, and prediction in the 'predict.py' script. The dataset used for this project work are of two types. The first type contains radiography images of children that are suffering from pneumonia. The second dataset contains the radiography image of children that are normal children. Samples of the radiography images of normal children used are presented in Figure 3, while images for children with pneumonia are presented in Figure 4. The model was trained for 10 epochs. The system achieved a training accuracy of 95.66% with a loss of 0.1135 and validation accuracy of 93.75% with a loss of 0.0854.

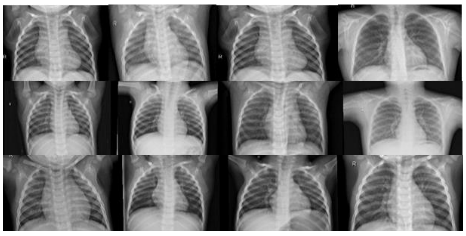

Figure 3. Radiographic image of normal children

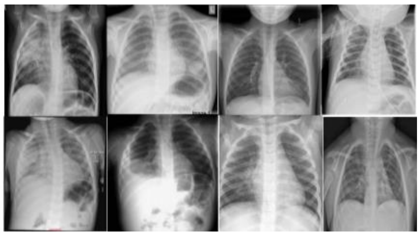

Figure 4. Children with pneumonia

7. EVALUATION OF THE MODEL

The metrics used for the model evaluation includes accuracy, precision, recall, and F1 score. From the results obtained, evaluation of the model on the test set yielded 88.14% accuracy, 90% precision, 85% recall and F1 score of 0.87 as presented in Figure 5. This is supported by the Confusion matrix presented in Table 2, where it is clear that out of 624 cases, presence of pneumonia was predicted 390 times and normal was predicted 234 times.

```
[49] score = model.evaluate(test_data_gen, verbose=1)

63/63 [==============================] - 7s 111ms/step - loss: 0.3678 - accuracy: 0.8814

              precision    recall  f1-score   support

      NORMAL       0.94      0.73      0.82       234
   PNEUMONIA       0.86      0.97      0.91       390

    accuracy                           0.88       624
   macro avg       0.90      0.85      0.87       624
weighted avg       0.89      0.88      0.88       624
```

Figure 5. Model evaluation results

8. THE CONFUSION MATRIX

The performance of a classifier on a set of test data from which the true values are known is often described using a confusion matrix. The confusion matrix in Table 2 shows the actual classes and the predicted classes for the cases in the test set in this work. From the table, the total predicted as normal is 234. The total predicted as pneumonia is 390. The total for actual normal is 180 while the actual pneumonia is 444.

Table 2. The confusion matrix

N = 624	Actual: normal	Actual: pneumonia	Total
Predicted: normal	170	64	234
Predicted: pneumonia	10	380	390
Total	180	444	

9. CONCLUSION

It can be concluded that using a pre-trained model reduces training time and yields better performance in the detection of pneumonia in chest radiographs. This further shows that deep neural networks with little data can be trained to achieve better recognition rate. Evaluation of the model developed on the test set yielded 88.14% accuracy, 90% precision, 85% recall and F1 score of 0.87. The model is very fast and can be used in medical department for analysis of chest radiographs for pneumonia detection. The model accuracy of 88.14% can still be improved upon by further training the network in order to improve its classification rate.

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