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Multi-Layered Convolutional Neural Network for Chest X-ray Images: Pneumonia Diagnostics Procedure

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Abstract- Convolutional neural network (CNN) models are beneficial to image classification algorithms training for highly abstract features and work with less parameter. Over-fitting, exploding gradient, and class imbalance are CNN major challenges during training; with appropriate management training, these issues can be diminished and enhance model performance. The study adopted convolutional neural network (CNN) Machine Learning (ML) model to determine, in diagnostics processes, using cardiology chest X-ray images, patients that are infected with pneumonia. The multi-layer model shows significant performance using anonymous volume of data sourced from Kagle.com machine learning database. A total of five thousand, two hundred and sixteen (5216) suspected pneumonia chest X-ray images were used for the training; while sixteen (16) separate images which were not used in the training was used to test the veracity of the model. The CNN model adopted in this work is a 256 by 256 layer CNN-ML training (or learning) and classification model. The output of the 256 by 256 CNN-ML model has the following evaluation results in consideration of mean values of error: (i) without validation, the accuracy was 94.56%; (ii) with validation, the accuracy was 95.82%; (iii) Absolute Error (AE) of 0.01263 and (iv) Relative Error (RE) of ± 0.01399. The study could be deplored in biomedical decision support system and patients' management in Covid-19 patient's diagnosis.

Keywords- *CNN, Multi-Layer, Pneumonia, Diagnostics and X-Ray*

I. INTRODUCTION

The needs for provision of bio-engineering solutions to problems in core non-engineering professions, as in medical and clinical practice, will continue as long as demands continue to exceed supply in terms of increasing rate of diseases. X-ray as a diagnostic means or tool has witness a great success in its repute for being a substantial; and reliable means of disease procedure and other health concerns diagnostics such as Covid-19. The level of expertise of medical professionals is also gradually and consistently being upgraded with mainstream input of artificial intelligence-AI (machine learning) and some other cases unreliable regarding the information that is deduced from the X-ray images [1].

The concept of disease burden studies focused pneumonia, regardless of cause, is a WHO initiative in which personnel from the Centers for Disease Control and Prevention (CDC) have been invited to facilitate the development of a generic protocol to be used to generate disease burden data for developing countries [2, 3].

The study focus more on deploring machine learning techniques to support pneumonia diagnosis clinical output and enhance cardiology patients' management.

II. LITERATURE REVIEW

A focus study of U.S. Department of Health and Human Services (HHS), with support from the Robert Wood Johnson Foundation, asked JASON to consider how AI will shape the future of public health, community health, and health care delivery. We focused on technical capabilities, limitations, and applications that can be realized within the next ten years [4]. This study shows how important AI and its machine learning applications are prized.

A. Medical imaging

Medical scans (X-rays), have been systematically collected and stored for some time and are readily available to train AI systems. AI application could reduce cost and time involved in analyzing scans, potentially allowing more scans to be taken to better target treatment procedures. AI has been proven promising results in decision support clinical procedures such as pneumonia, cancers, and eye diseases [5]. Fig. 1 and 2 are examples of typical chest X-ray images in pneumonia diagnosis.

Figure 1. Showing Middle and Lower lobe consolidation in right lung

Figure 2. Showing Pulmonary Nodule in right lung [6]

B. *Artificial Neural Network*

The various artificial neural network used in machine learning are increasingly being modified for better performances.

1) Feedforward Neural Network – Artificial Neuron:

This neural network is one of the simplest forms of ANN, where the data or the input travels in one direction. The data passes through the input nodes and exit on the output nodes. This neural network may or may not have the hidden layers. In simple words, it has a front propagated wave and no back propagation by using a classifying activation function usually. A multilayer perceptron is a type of feedforward neural network [7].

2) Radial basis function Neural Network:

Radial basic functions consider the distance of a point with respect to the center. RBF functions have two layers, first where the features are combined with the Radial Basis Function in the inner layer and then the output of these features are taken into consideration while computing the same output in the next time-step which is basically a memory [8].

3) Deep learning

Deep learning could be adapted into computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction [9]. This could be deployed in speech recognition, visual object detection and recognition with respect to initial input and internal parameter (weight). Deep learning was firstly introduced by Hinton et al [10] for a class of deep probabilistic generative models called Deep Belief Networks (DBNs) [11].

4) Convolutional Neural Network

In deep learning, a convolutional neural network (CNN) is a class of deep neural networks, most commonly applied to analyzing visual imagery. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics [12, 13]. They have applications in image and video recognition, recommender systems, [14] image classification, medical image analysis, natural language processing, [15] and financial time series [16].

5) Convolutional layer

The convolutional layer is core building block of a CNN model; and layer's parameters consist of a set of learnable filters (or kernels) with small receptive field, but extend through the full depth of the input volume including internal parameter. During the forward pass, each filter is convolved across the width and height of the input volume, computing the dot product between the entries of the filter and the input and producing a 2-dimensional activation map of that filter. As a result, the network learns filters that activate when it detects some specific type of feature at some spatial position in the input. Fig. 3 shows a typical CNN layer configuration.

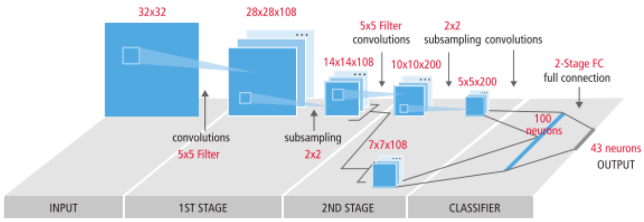

Figure 3. Typical CNN Layer Configuration [17]

6) TensorFlow Library

It is an open source artificial intelligence library, using data flow graphs to build models. It allows developers to create large-scale neural networks with many layers. TensorFlow is mainly used for: Classification, Perception, Understanding, Discovering, Prediction and Creation [18]

7) Keras Platform

Keras is an open-source neural-network library written in Python language which uses TensorFlow as its backend. It is capable of running on top of Microsoft Cognitive Toolkit, R, Theano, or PlaidML. Designed to enable fast experimentation with deep neural networks, it focuses on being user-friendly, modular, and extensible [19].

8) Related Works

According to Chumbita *et al*, (2020) "Can Artificial Intelligence Improve the Management of Pneumonia" adopted reviewed methods used to predict pneumonia procedure using artificial intelligence. It is worthwhile to note that, while the work will serve as a glossary of present day AI applications in medical X-ray images, it will not be a method adopted into any diagnostics processes [1].

Garima Verma and Shiva Prakash in their paper, endeavored to classify pneumonia infections using X-ray images. The processes of various operations carried out on the dataset prior to actual training makes it prone to degradation of vital features of the image [21].

III. Method

The study implemented and trained segmentation and classification algorithm; performed on an AMD Quad-Core 1.7GHz processor on a 64-bit windows 7 operating system with 6.0 GB RAM using Python and Jupyter Notebook. The trained data acquired was of size 120 by 100 pixels, the image slices were resized to 50 by 50-pixel size before extracting features from the images. All the images supplied were passed through Open CV [22]. (Open CV, 2020) preprocessing steps to enhance its contrast as pure gray scale. The Convolutional Neural Network Machine Learning (CNN-ML) model was made of: 256 by 256 CNN-ML model. The study evaluated the training (or learning) and classification results for the model. Fig. 4 shows image operation in CNN.

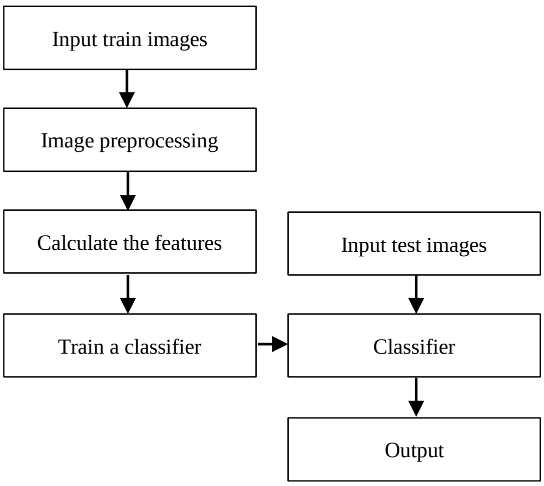

Figure 4. Artificial Neural Network model block diagram for image processing and classification [23].

The neural network operation can be expressed with equations (1 - 4). In equation (1), Y is the initial summation of the output of the neural network model.

$$Y = \Sigma\,(weight * input) + bias \quad (1)$$

Equation (2) expresses the convolution of the individual input with their respective associated weights.

$$z = x_1 * w_1 + x_2 * w_2 + \cdots + x_n * w_n + b * 1 \quad (2)$$

The overall (final) output $\hat{y}$, got from the sigmoid binary classification function, is expressed in (3)

$$\hat{y} = a_{out} = sigmoid\,(z) \quad (3)$$

The mathematical expression of the sigmoid function is given in (4)

$$sigmoid\,(z) = \frac{1}{1 + e^{-z}} \quad (4)$$

The neural network layer is broadly divided into three basic layers as in fig. 5.

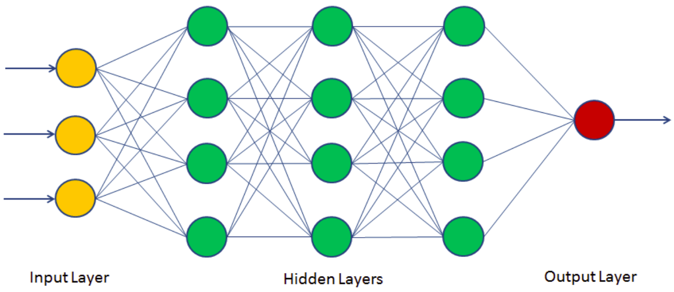

Figure 5. Neural Network layer block diagram

IV. Results and Discussions

A. Training Phase of the Model

The sourced X-ray images were of sizes greater than 1000 by 1000 pixels; these image slices were resized to 50 by 50 pixel size before acquiring characteristics features from the images. A Convolution Neural Network Machine Learning (CNN-ML) model was adopted, a 256 nodes by 256 nodes CNN-ML model for training (or learning) and classification and evaluated the result for the classifier. The result of the training is presented as follows:

Fig. 6 and 7 show the original X-ray image and the normalized image respectively.

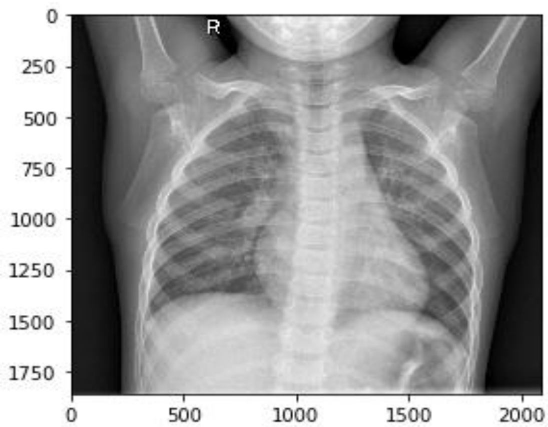

Figure 6. Sourced X-ray image

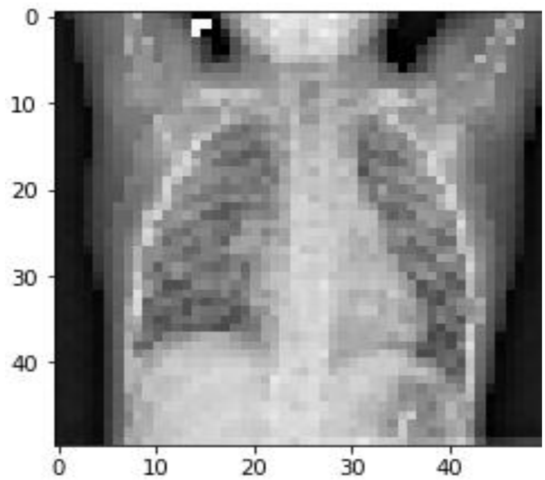

Figure 7. Normalized X-ray image

Table one (1) shows the training output without validation. From the table, it can be seen that the loss at the initial stage was 0.4692, but as the training progresses per batch, the loss was diminished to 0.0595. The accuracy on the other hand, was progressively increasing as time elapsed from a value of 0.7825 to 0.9783. This goes to show the inverse relationship between accuracy and loss, for progressive training. As loss decreases, accuracy increases.

TABLE I. TRAINING RESULTS FOR THE MODEL DATASET WITHOUT VALIDATION

Epoch	Batch Size	Time Elapsed (seconds)	Loss per batch	Accuracy per batch
1/10	100	1414	0.4692	0.7825
2/10	100	1401	0.1799	0.9293
3/10	100	1403	0.1152	0.9555
4/10	100	1403	0.0988	0.9604
5/10	100	1407	0.0874	0.9659
6/10	100	1404	0.0759	0.9691
7/10	100	1402	0.0784	0.9706
8/10	100	1405	0.0744	0.9721
9/10	100	1405	0.0759	0.9723
10/10	100	1405	0.0595	0.9783

Table two (2) shows the output of the training with validation of the process. It is observed that from the table initial loss was much lower than that of Table 1 but with a comparative higher loss at the end of the training. The accuracy on the other hand, shows improvement on both the initial and final values.

TABLE II. TRAINING RESULTS FOR THE MODEL DATASET WITH VALIDATION

Epoch	Batch Size	Time Elapsed (seconds)	Mini-batch Loss	Mini-batch Accuracy
1/10	100	1414	0.2208	0.8927
2/10	100	1401	0.1606	0.9425
3/10	100	1403	0.0855	0.9636
4/10	100	1403	0.0963	0.9617
5/10	100	1407	0.0769	0.9789
6/10	100	1404	0.0690	0.9770
7/10	100	1402	0.0890	0.9713
8/10	100	1405	0.1322	0.9540
9/10	100	1405	0.0834	0.9617
10/10	100	1405	0.0710	0.9789

B. *Evaluation Phase of the Trained Model*

To evaluate the model performance, a confusion matrix table was developed to calculate the accuracy, precision, sensitivity, specificity and effectiveness. The following labels have been used in the table: TP (True Positive), FP (False Positive), TF (True Negative) and FN (False Negative).

TABLE III. THE CONFUSION MATRIX TABLE FOR THE X-RAY IMAGE USED FOR TESTING THE MODEL

	Pneumonia (predicted)	Not Pneumonia (predicted)
Pneumonia (actual)	TP = 6	FN = 2
No Pneumonia (actual)	FP = 0	TN = 8

The evaluation parameters are calculated as follows:

(i) Accuracy (A) = $\frac{TP+TN}{TP+FN+FP+FN}$ (5)

(ii) Precision (P) = $\frac{TP}{TP+FP}$ (6)

(iii) Sensitivity (Se) = $\frac{TP}{TP+FN}$ (7)

(iv) Specificity (Sp) = $\frac{TN}{TN+FP}$ (8)

(v) Effectiveness (E) = $\frac{2XPrecisionXSensitivity}{Precision+Sensitivity}$ (9)

The result of applying equations 5 – 9 on Table 3 is shown in Table 4.

TABLE IV. EVALUATION RESULT OF THE TESTING PHASE

A	P	Se	Sp	E
0.875	1.00	0.75	1.00	0.857

1) Error Analysis of the Model

The average values of the error calculations have been summarized in Table 5. In this study, the following types of errors were considered:

The average values of the error calculations have been summarized in Table 5. In this study, the following types of errors were considered:

a) Absolute Error (AE)

This is the absolute difference between the model value and the manual value

$$AE = |Model\ with\ Validation - Model\ without\ Validation| \quad (10)$$

The mean absolute error (AE) has a value of 0.01263 as shown in Table 5.

b) Relative Error (RE)

$$\text{RE} = \frac{AE}{Model\ Value} \quad (11)$$

The mean relative error (RE) has a value of 0.01399

TABLE V. PERFORMANCE ERROR ANALYSIS FOR THE TRAINING AND VALIDATION

Sample Batch Image Number	Model without Validation Acc.	Model With Validation Accuracy	Absolute Error (AE)	Relative Error (RE)
1	0.7825	0.8927	0.1102	0.123446
2	0.9293	0.9425	0.0132	0.014005
3	0.9555	0.9636	0.0081	0.008406
4	0.9604	0.9617	0.0013	0.001352
5	0.9659	0.9789	0.013	0.01328
6	0.9691	0.9770	0.0079	0.008086
7	0.9706	0.9713	0.0007	0.000721
8	0.9721	0.9540	0.0181	0.01897
9	0.9723	0.9617	0.0106	0.01102
10	0.9783	0.9789	0.0006	0.000613
MEAN	0.9456	0.95823	0.01263	0.013991

V. CONCLUSION

This study shows how machine learning (AI), in the aspect of convolutional neural network can be deplored to support diagnostic clinical output involving cardiology X-ray images to towards pneumonia clinical decision and other chest opportunistic infections such Covid-19 and Chronic Obstructive Pulmonary disease - COPD. The model comprises of a training phase and a testing phase. The testing phase is wholly dependent on the trained (learned) model. The outputs of the model show that the validated model has higher accuracy value of 0.9582 as compared to that without validation having a value of 0.9456 with a margin difference of 0.013. This diagnostic model could be embedded in future chest X-ray images diagnostic machines. A further study can be done in the aspect of improving the system throughput including timeframe to enhance clinical decision and patients' management.

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