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Pneumonia Detection through Adaptive Deep Learning Models of Convolutional Neural Networks

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***Abstract*— An infectious illness known as Pneumonia is often caused by infection due to a bacterium in the alveoli of lungs. When an infected tissue of the lungs has inflammation, it builds up pus in it. To find out if the patient has Pneumonia, experts conduct physical exams and diagnose their patients through Chest X-ray, ultrasound, or biopsy of lungs. Misdiagnosis, inaccurate treatment, and if the disease is ignored, it may lead to the death of a patient. The progression of Deep Learning contributes to the aid in the decision-making process of the experts to diagnose patients with pneumonia. The study employs flexible and efficient approaches of deep learning applying six models of CNN in predicting and recognizing a patient unaffected and affected with the disease employing a chest X-ray image. GoogLeNet, LeNet, VGG-16, AlexNet, StridedNet, and ResNet-50 models with a dataset of 28,000 images and using a 224x224 resolution with 32 and 64 batch sizes are applied to verify the performance of each models being trained. The study likewise implements Adam as an optimizer that maintains an adjusted 1e-4 learning rate and an epoch of 500 employed to all the models. Both GoogLeNet and LeNet obtained a 98% rate, VGGNet-16 earned an accuracy rate of 97%, AlexNet and StridedNet model obtained a 96% while the ResNet-50 model obtained 80% during the training of models. GoogleNet and LeNet models achieved the highest accuracy rate for performance training. The six models identified were capable to detect and predict a pneumonia disease including a healthy chest X-ray.**

Keywords—Pneumonia Detection, Adaptive Deep Learning, Deep Convolutional Neural Network Architecture

I. INTRODUCTION

Pneumonia is an ailment that distracts the passage of air in the lung air sacs of an infected person due to tissue inflammation that causes by the accumulation of fluids or pus[1]. Pneumonia is usually triggered by bacterium, fungus, or virus that infects the alveoli of lungs that develops fluid discharges especially to persons experiencing coldness, arising body temperature, and breathing problems due to stuffy nose. Elderly persons aging from 50 years old and above and children below five years of age have a weaker immune system and they are susceptible to this kind of illness. This type of disease has claimed over a million lives of both children and the elderly globally in 2017 and it continues a deadly sickness nowadays if not detected at an earlier time [2]. The disease can be learned using Radiography, CT-scan, or MRI and among these processes, radiograph or chest X-ray is the most popular practice in a health examination. Experts take an image of the chest of the patient through a chest X-ray or radiograph. A radiograph is an image produced on a thin-skinned film using radiation to confirm or validate the person infected by pneumonia or not. Also, experts diagnose their patients through their medical history and laboratory results.

X-ray produces a dark color on the radiograph as it penetrates the soft tissue of the chest while X-ray penetration on the hard tissues like the bones of humans produces a bright color by lowering the X-ray intensity level. As shown in figure 1 on the left image, the chest cavity which is translucent visible or dark color because the lung cavities contain air. If the patient is diagnosed with pneumonia as seen in figure 1 on the right, the radiograph image of the chest cavity looks brighter as fluids fill the air sacs. Several abnormalities in the lung cavity are characterized in a brighter color that may contain cancer cells, blood vessels swelling, pneumonectomy, and irregularities of the heart [3].

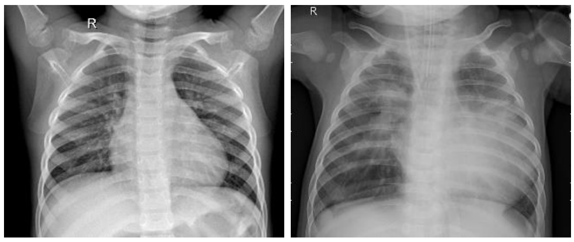


Fig. 1. Normal Chest X-ray in left and pneumonia infected Chest X-ray in right.

Computer-aided detection (CAD) has existed and this tool has emerged so fast. The primary goal of CAD is to assist medical experts in the decision-making process and interpretation through validation using a computer system [3]. Using CAD may aid in improving the accuracy of diagnosis, lessen the workload of experts, and improve reading variability. Computer vision and deep convolutional neural networks present image-segmentations, feature-extractions, and classification that is integrated into the CAD systems.

Image classification [4] and disease detection [5] are some identified innovations of Deep convolutional architectures since it can incorporate image information both in lower and higher features. The processed information can be further enhanced through additional stacked layers [6]. In the study, the researchers conducted six known CNN architectures. These are the LeNet, GoogLeNet, VGGNet-16, AlexNet, StridedNet, and ResNet-50 models. Each model in the networks is optimized to enhance the performance of those networks of prior developed architecture.

The primary aim of this paper is as follows:

• Identify the among the six identified CNN models, the top model for pneumonia detection through adaptive deep learning models of CNN.

• Evaluate each model in terms of accuracy performance using hyperparameters and optimization in pneumonia detection.

II. RELATED WORKS

Medical images utilizing CAD systems are been used in decades ever since the age of artificial intelligence. Since then AI technology has been elevated to machine learning and to deep learning that resulted in an improved acceleration through its performance. This developed technology turns to different techniques like classifying diseases of human-related, animals, and plant diseases. With an increased quantity of datasets used, Deep CNN has been the highly recommended used techniques for identifying and classifying numerous types of medical-related images.

A. Deep Learning

Learning from the Deep Learning point of view is a method of cultivating the actions based on knowledge and experience. Deep Learning is an artificial intelligence and machine learning subgroup which expands the output of countless machine learning applications like AI. Deep architecture technique organized with many processing parts [7] that started in the early 1960s has affected non-linearity and computing power based on the GPU via acceleration, allowing for deeper networks that have better used their resources [8]. Deep architectures composed of numerous hidden-layers improve the neural network's overall performance. Since the 1980s and up to date the invention of back-propagation is still utilized to preserve the neural network [9]. Classifying the medical images is a very exciting and inspiring job to perform until now. The work of M. Anthopoulos et.al. detects six classes of diseases and 1class is not tissue infected, classifies the Interstitial Lung Diseases (ILDs) using deep learning techniques [10]. Another work introduces a machine called Boltzmann machine that analyzes diseases through the lung generated tomography (CT) [11]. The study uses two datasets to introduce two unique techniques, the texture classification and detection of airways P. Moeskops and. Al. uses several kernel-based CNN networks to rate patient brain organs [12]. The work of Z. Yan et.al. uses a dual framework for instance, first, CNN is applied for extraction and the extracted features are used for classification of images [13]. The study utilizes 12 classes of CT and MR images.

The authors in another study developed numerous models to confirm an accurate result of the top model in detecting pneumonia [14]. Their study trained AlexNet, LeNet, GoogleNet, ResNet, and VGGNet of CNN models using a 1024x1024 image resolution using a dataset of 26,684 images. The result of their study reached a 97% accuracy rate for VGGNet and 74% is the lowest rate attained by the ResNet model [14].

B. Convolutional Neural Network

Stimulated by the human brain, the convolutional neural network is a feed-forward neural network. It is capable of extracting characterized features and classifies them. CNN's conventional architecture is illustrated in figure 2.

The standard convolutional layer acquires image input that creates map features through the kernel. It works by taking each neuron from the preceding layer. Increased performance of improved illustration of images because of multiple neuron connections and overlapping with each other. Weight sharing reduces the number of parameters. Every connected convolutional layer to nonlinear activation layer accelerates CNN in more complex functions that may lead to overfitting and pooling is used to overcome the overfitting and reduce also the number of parameters and fully-connected layers summarize the trained features to provide the classified result.

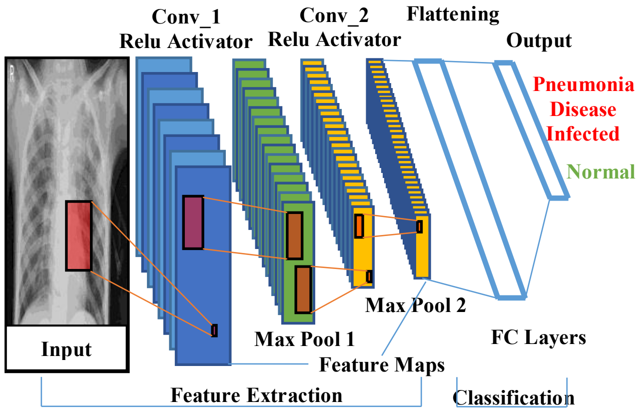


Fig. 2. Convolutional Neural Network Model Processing

Numerous authors have been using several CNN models in their research. The plain and simple architecture was developed using the LeNet model [15] was introduced in the works of Le Cun et.al. They modified layers, kernels, optimizers, and hyper-parameters to train their model. In their proposed model, composed of several kernels in one convolution learns extra complex functions that compute multiple map features with activation and pooling layers.

III. PROPOSED METHODOLOGY

Illustrated in this segment are pneumonia collected images, pre-processed images, and various CNN architectures utilized in this study. Latter subsections discuss the details of the used method in each step of the study framework as shown in figure 3.

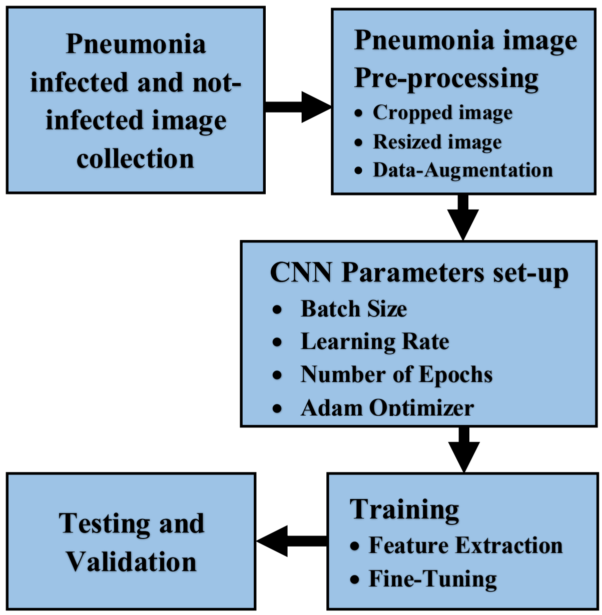


Fig. 3. Pneumonia Recognition Framework

A. Pneumonia Dataset Collection

Chest X-Ray examinations are quite interesting jobs in the field of health science. There are spontaneously obtainable chest X-Ray datasets but they are up to a few thousands of images available [16]. The study employed the dataset of the

Radiological Society of North America (RSNA) which consists of a total of 28,000 chest X-Ray images that are publicly available [16] [17]. It is formatted in a JPEG format and categorized into two classes namely; pneumonia disease-infested and not infested with pneumonia disease chest X-Ray as displayed in figure 4. The images have maximum dimensions of 1024 x 1024 resolutions.

Fig. 4. Pneumonia Dataset Collection

B. Pneumonia Image Preprocessing

Pneumonia image preprocessing is the succeeding stage in the pneumonia detection framework of the study. All chest X-Ray images acquired are independently cropped to generate a uniform measurement. To satisfy the required input for CNN architectures, all cropped images are resized to 224x224 square pixels. The collected data were labeled properly by experts for precise labeling in classification and they are divided into 80:20 for training and testing.

C. CNN Models

This stage describes the use of CNN architectures for modeling pneumonia disease detection.

1. AlexNet model

AlexNet won an ImageNet Challenge which was developed by A. Krizhevesky for visual object recognition in 2012 [10]. It is the most studied architecture of CNN [18] for classification tasks on images [18]. AlexNet structure has 5 convolutional layers, 2 fully-connected layers with max pooling, and the activation layer that connects to 1000 classes. Its parameters comprise of 61 million.

2. GoogLeNet model

GoogleNet architecture's goal is by learning with its parameters reduced. It is inspired based in Inception architecture with a total of 22 convolutional layers [19] using small convolutions, small-batch normalizations. Its parameters comprise of 4 million.

3. LeNet model

LeNet architecture comprises of 2 convolutional, pooling-layers with a flattened convolutional layer, 2 fully-connected layers, and softmax classifier. LeNet is straightforward and small, making it perfect for teaching the basics of CNNs, it can run on the central processing unit (CPU) even if your system does not have a suitable graphical processing unit (GPU). LeNet parameter consists of 60 thousand parameters only.

4. StridedNet model

StridedNet architecture employs stride convolutions for lower volume size, the use of batch normalization, and hyper-parameters fine-tuning to improve training accuracy. The utilization of dropout is to help the network generalize and minimizing overfitting. The stridedNet parameter is approximately 1 million.

5. ResNet-50 model

ResNet consists of 3 convolutions for a total of 75 layers deep in every convolution block and combines several sizes of convolution kernels with residual blocks during training to lessen training time. Its parameters comprise of 61 million.

6. VGGNet-16 model

Simonyan and Zisserman introduced VGG network architecture in 2014. VGG-16 architecture consists of 16 convolutional layers, 2 fully-connected layers with 4,096 nodes for each layer. Its parameters comprise of 138 million and considered the most used image-detection architectures.

D. Transfer Learning and Fine-Tuning

Fine-tuning is the final method in the training of models. Feature extraction is used in the first layers of each CNN architectures and the last few layers are intended for learning. Pneumonia infected disease and not infected with the disease learned from every class are implemented in each architecture and the remaining layers of each architecture are changed with the same kind of layers however with another parameter.

IV. RESULTS AND ANALYSIS

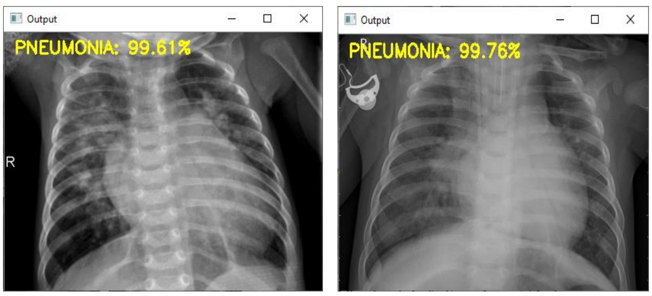
We have assessed the performance of six CNN architectures namely; AlexNet, GoogleNet, LeNet, StridedNet, ResNet-50, and VGGNet-16. The performance testing results are very acceptable since all six models attained a 96% to 98% accuracy rate during training with the given input parameters. The highest record was 98% were realized by GoogleNet and LeNet models, 97% mark was obtained by VGGNet-16 while StridedNet and AlexNet model has both 96% mark using both 32 and 64 batch-sizes. The lowest recorded rate was attained by the ResNet-50 model with a rate of 80%. Demonstrated in Table 1 is the assessment of performance models during the conduct of training using a batch-size of 32 at 500 epochs of the six (6) CNN models. Table 2 demonstrates the assessment of performance models during the conduct of training using a batch-size of 64 at 500 epochs. All the tests conducted were completed using a laptop computer with a speed of up to 4.2 GHz containing 12 logical cores and a memory of 16 GB and a GTX 1050 video card. Data augmentation methods are also incorporated to intensify the dataset. Image rotation, image flipping, zoom, and shifting are only some of the methods applied. Optimization using Adam and categorical cross-entropy are some features set to all models. A 32 and 64 batch-sizes for five hundred times were also set for all the models with a learning rate of 1e-4 during the training of models. The training and validation accuracy and loss result of six trained CNN architectures is displayed in Table 3 with batch size of 32 and epochs of 500 while Table 4 shows the result of batch size of 64 and epochs of 500. The result of predicting several images of pneumonia disease with predicted percentage value is shown in figure 5 using 6 different CNN models. While in figure 6 are sample images with its corresponding predicted percentage results of a normal chest X-Ray using the six identified CNN models.

TABLE 1. ASSESSMENT OF MODEL PERFORMANCE FOR CNN MODELS WITH 32 BATCH SIZE

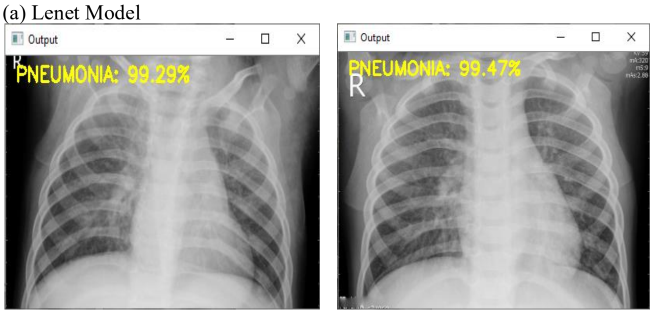
CNN Model	Batch Size	Criterion	Normal	Infected with Pneumonia
AlexNet	32	Precision	0.78	1.00
		Recall	1.00	0.88
		F1-score	0.85	0.94
GoogLeNet	32	Precision	1.00	0.99
		Recall	0.99	1.00
		F1-score	0.99	0.98
LeNet	32	Precision	1.00	0.99
		Recall	0.99	1.00
		F1-score	0.99	0.98
ResNet-50	32	Precision	0.85	0.85
		Recall	0.87	0.84
		F1-score	0.83	0.80
StridedNet	32	Precision	0.98	0.99
		Recall	0.98	0.97
		F1-score	0.95	0.96
VGGNet-16	32	Precision	0.99	0.98
		Recall	0.97	0.98
		F1-score	0.97	0.98

TABLE 2. ASSESSMENT OF MODEL PERFORMANCE FOR CNN MODELS WITH 64 BATCH SIZE

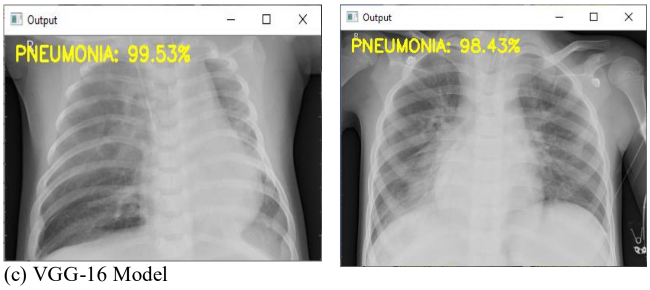
CNN Model	Batch Size	Criterion	Normal	Infected with Pneumonia
AlexNet	64	Precision	0.80	0.99
		Recall	0.89	0.84
		F1-score	0.86	0.92
GoogLeNet	64	Precision	0.98	0.99
		Recall	0.99	1.00
		F1-score	0.97	0.99
LeNet	64	Precision	0.98	0.97
		Recall	0.97	0.99
		F1-score	0.96	0.98
ResNet-50	64	Precision	0.84	0.80
		Recall	0.82	0.83
		F1-score	0.82	0.78
StridedNet	64	Precision	0.97	0.95
		Recall	0.96	0.97
		F1-score	0.93	0.94
VGGNet-16	64	Precision	0.98	0.97
		Recall	0.96	0.95
		F1-score	0.94	0.95



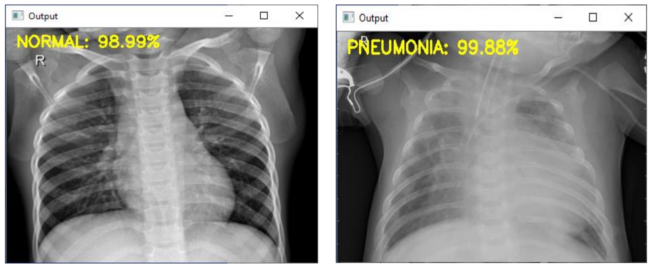
(a) Lenet Model



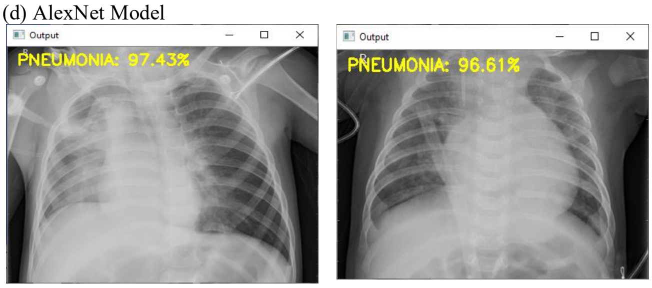
(b) GoogleNet Model



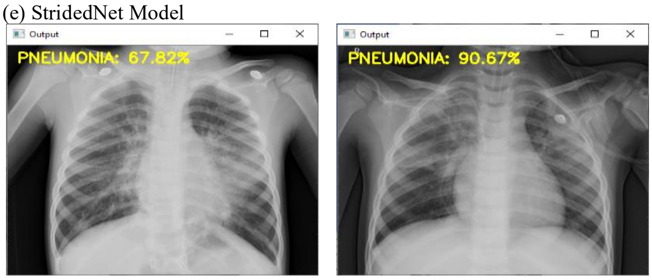
(c) VGG-16 Model



(d) AlexNet Model

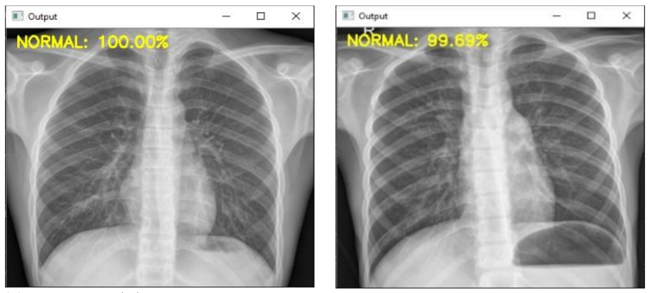


(e) StridedNet Model

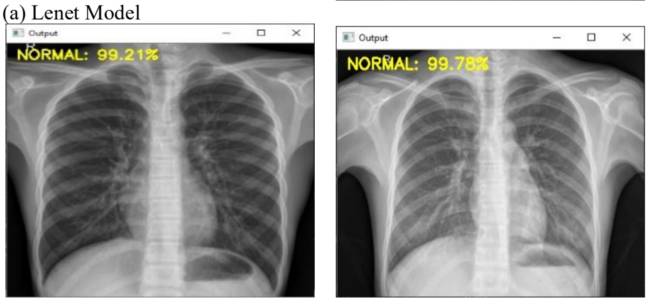


(f) ResNet Model

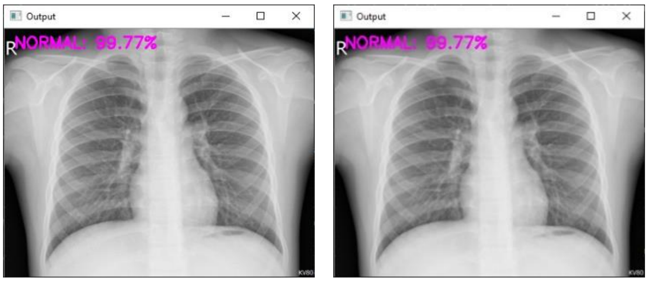
Fig. 5. Shows the result of predicted images of pneumonia infected disease using six different CNN models



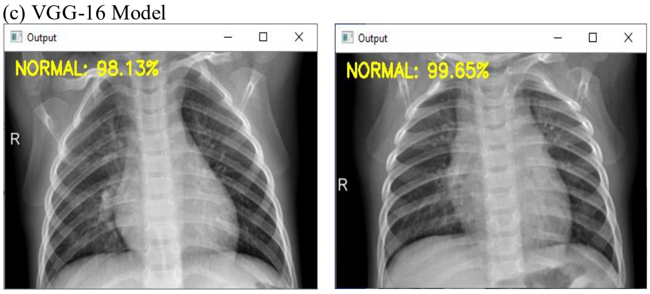
(a) Lenet Model



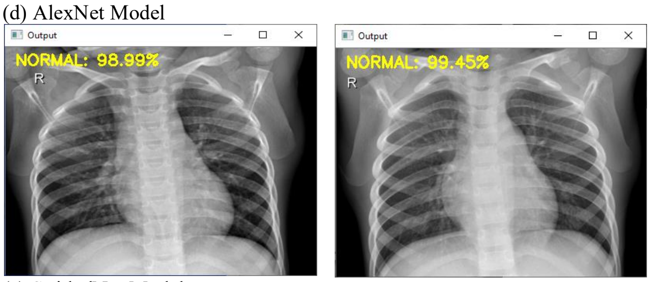
(b) GoogleNet Model



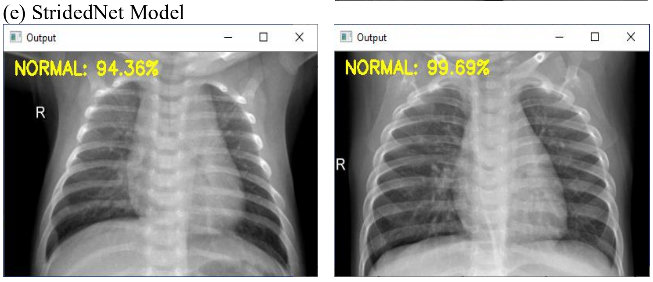
(c) VGG-16 Model



(d) AlexNet Model



(e) StridedNet Model



(f) ResNet Model

Fig. 6. Shows the result of predicted images of a Normal Chest X-Ray using six different CNN models

TABLE 3. TRAINING PERFORMANCE END RESULT OF SIX TRAINED CNN ARCHITECTURES WITH BATCH SIZE OF 32 AND EPOCHS OF 500

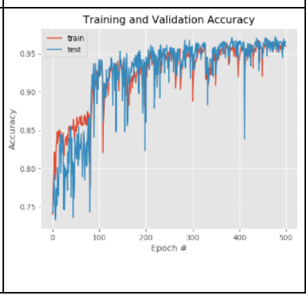
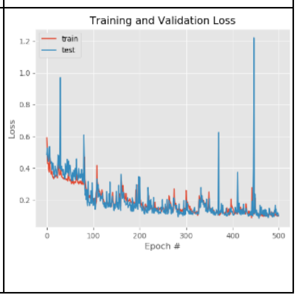
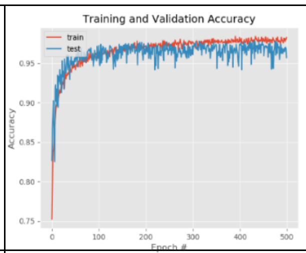
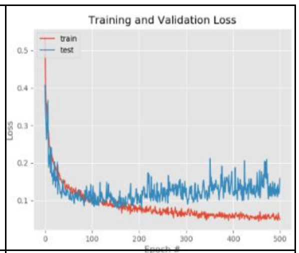
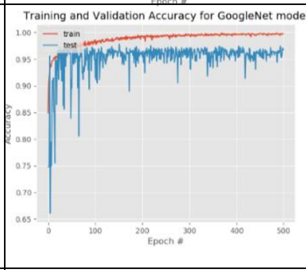
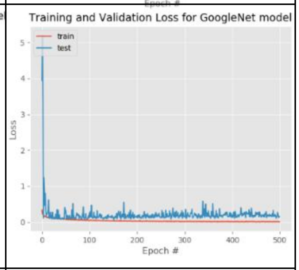
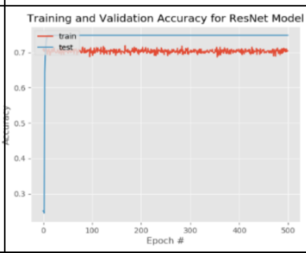
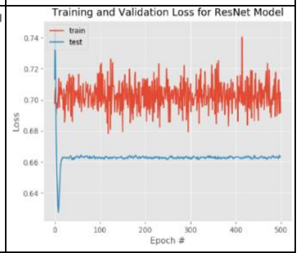
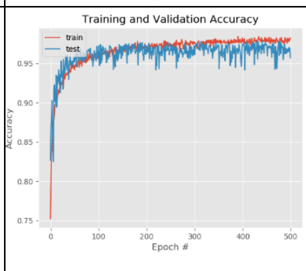
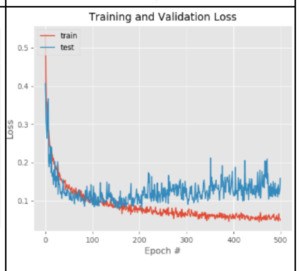
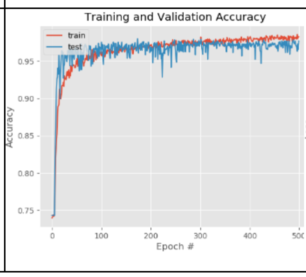
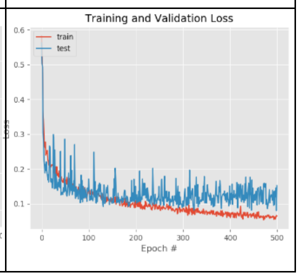
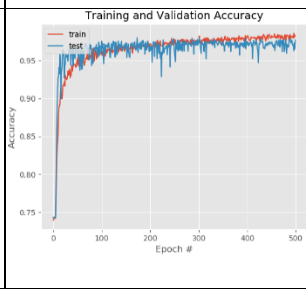
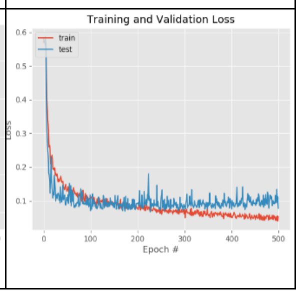
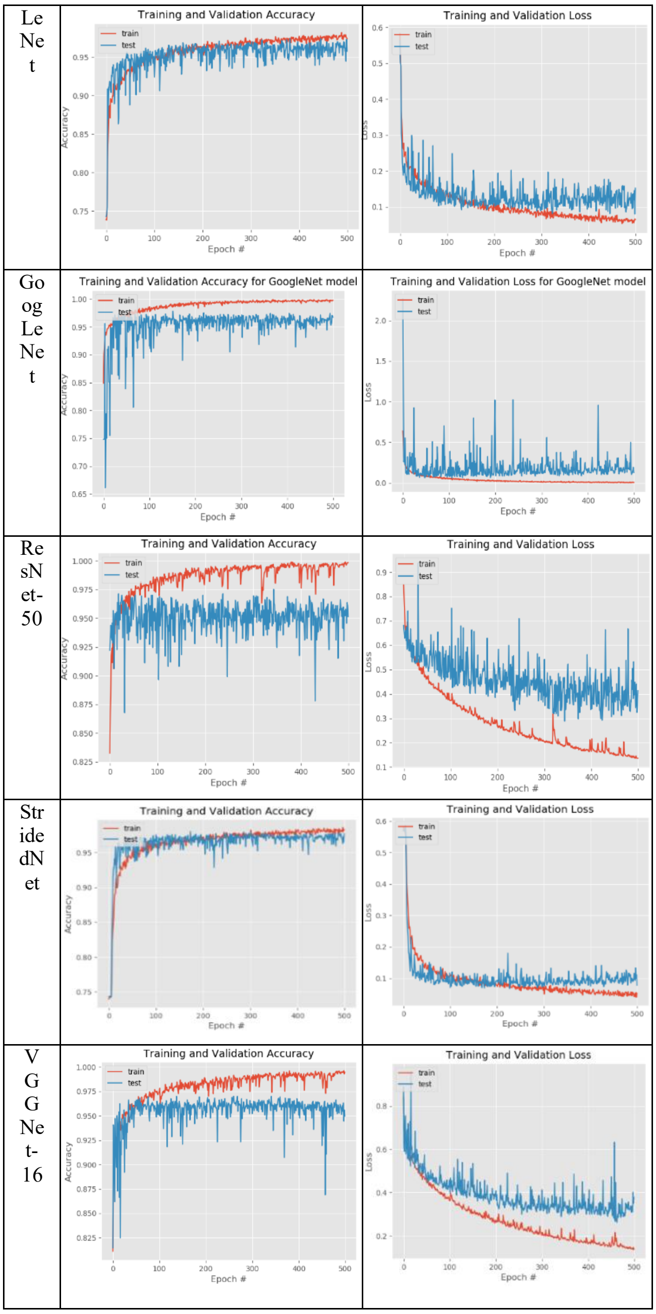
Model	Training and Validation Accuracy	Training and Validation Loss
AlexNet		
LeNet		
GoogLeNet		
ResNet-50		
StridedNet		
VGGNet-16		

TABLE 4. TRAINING PERFORMANCE END RESULT OF SIX TRAINED CNN ARCHITECTURES WITH BATCH SIZE OF 64 AND EPOCHS OF 500

Model	Training and Validation Accuracy	Training and Validation Loss
AlexNet		



V. CONCLUSIONS

Computer vision and deep learning techniques play a major role in these researches to detect pneumonia adapting six CNN models. All the six identified CNN models were evaluated substantially to collect for feature extraction and fine-tuning for its framework. The aim of the study was realized that the researchers were able to categorize among the six models is the best model to identify pneumonia disease. GoogLeNet and LeNet are the top models based on performance accuracy of 98% while the ResNet-50 gained the last among the six models trained with an accuracy rate of 80%. VGG-16, AlexNet, and StridedNet achieved a very satisfactory performance with a mark of 96% to 97%. The six models performed well on detecting pneumonia and consider the great process in diagnosing and detecting pneumonia which benefits the medical experts in providing a high-quality medical service to their patients.

For future studies, an adaptation of other convolutional neural network architectures like Inception-v3, shuffle Net, and Mobile Net architectures for pneumonia detection must be implemented and the optimization of hyper-parameters should also be considered to improve the accuracy of the model.

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