An Innovative Approach Of Detecting Pneumonia Using Transfer Learning

Rajinder Tiwari[1]*, Gurpreet Raina[2], Abdul Saboor[3]

Abstract

Due to bacterial, viral, or fungal infection, pneumonia is a fatal lung condition known as the "silent killer," which results in the lungs being disorganized and fluid filled. Chest x-rays are the most popular way to diagnose pneumonia, and a doctor is required to accurately interpret the results of an x-ray. The creation of an energy-efficient medical system with an autonomous pneumonia detection approach will play a significant role in improving the healthcare system with lower costs and better reaction times. Pneumonia is one of the most targeted health issues in the modern technological era. Pneumonia is a lethal lung ailment known as the "silent killer," which results in the lungs becoming disorganized and filling with fluid. It is brought on by a bacterial, viral, or fungal infection. Chest x-rays are the most popular way to diagnose pneumonia, and a doctor is required to accurately interpret the results of an x-ray. An important part of enhancing the healthcare system with reduced costs and faster response times will be the development of an energy-efficient medical system with an autonomous pneumonia detection strategy. In the current technology era, pneumonia is one of the most targeted medical conditions.

Keywords: Pneumonia, X-Rays, CNN, Resnet50, VGG19, Transfer Learning.

DOI Number: 10.48047/NQ.2022.20.17.NQ880208 **Neuroquantology 2022; 20(17):1696-1701**

INTRODUCTION

All old and young individuals worldwide are affected by pneumonia, although Sub-Saharan Africa and South Asia have the highest rates of infection. Engineers and researchers may now obtain cutting-edge computer vision products because to neural networks' rapid rise in popularity. Due to Deep Learning technology and Artificial Intelligence aids it is possible to automate analytical methods. Pneumonia exposure is relatively high for many people, especially in poor and economically undeveloped nations where the majority lack access to a healthy diet. More than 4 million avoidable deaths each year are caused by diseases associated to air pollution, according to the World Health Organization.

This illness can be broadly divided into three categories: bacterial, fungal, and viral. Young individuals and the elderly are both affected by pneumonia. If untreated, pneumonia can be fatal and lead to respiratory infections as well as other respiratory issues. If not treated in a timely manner, fluid and pus buildup in the lungs might further impair a person's health. Exposure to pneumonia is fairly common today, especially in underdeveloped countries. According to the World Health Organization, air pollution-related illnesses cause more than 4 million avoidable deaths each year. Artificial intelligence enables us to automate analytical methods thanks to deep learning technologies. Since lives may be at stake, the AI models should be as accurate as possible. In the past, it has been noted that doctors have provided falsely positive or falsely negative results, which has led to the patients' poor medical conditions. The advantage in these models is that apart from predicting pneumonia, it is possible to classify patients with Viral or Bacterial Pneumonia with high accuracies which leads to faster medical treatment. It has been seen by researchers that CNN is the

***Corresponding author: -** Rajinder Tiwari
Address:-[1*,2,3]Department of Electronics & Communication Engineering, Model Institute of Engineering & Technology [Autonomous], Jammu, J&K, India,
E-mail:- rajinder.tiwari@ieee.org[1], gurpreetraina.ece@mietjammu.in[2], abdul.57-ece-18@mietjammu.in[3]
Relevant conflicts of interest/financial disclosures: - The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

ultimate choice when working with any image and hence widely used in these classification problems [2]. This paper's goal is to provide two AI models that can accurately categorise X-rays into three categories (Bacterial Pneumonia, Viral Pneumonia, and Normal) and compare the findings with earlier research.

BACKGROUND OF ML ALGORITHMS

As stated above convolutional networks are primarily chose to recognize pattern and faces. A CNN is made up of an input layer, an output layer, and several hidden layers in between, similar to other neural networks. Convolutional Neural Network (CNN) in CNN conducts feature extraction on pictures before categorizing them using a particular algorithm. It accepts input in the form of photos, processes them, and produces a result based on our datasets. For training, it will correctly categorize the pictures by running them through a number of convolutional layers, filters, and pooling layers. CNN is most known as a kind of feed forward network. [3] which was earlier used for recognition of handwritten zip code digits

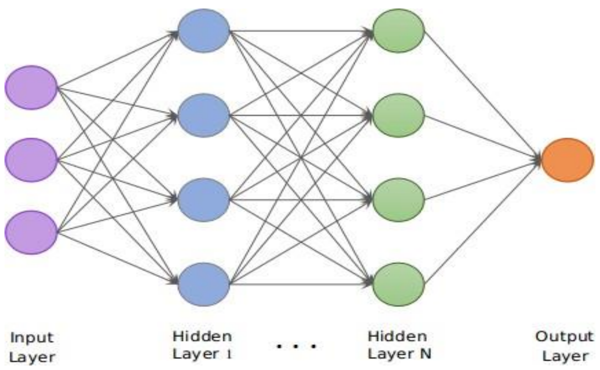


Figure 1: Hidden layers of CNN architecture

Transfer Learning

The machine learning method known as transfer learning uses a model built for one task as the basis for another task. Pre-trained models serve as the foundation for deep learning techniques used in computer vision. A stored network that has previously been trained on a significant dataset, generally on a sizable image classification problem, is referred to as a PRE-TRAINED MODEL.

ResNet

Resnet is a type of pretrained model from the Keras and has the advantage to allow us to use weights that are already calibrated to make predictions. There are three types of ResNet as ResNet101, ResNet50, ResNet18 and the digits associated with them are the number of network layers they have. A well-known model ResNet50 for pneumonia detection was considered [4]. ResNet50 is convolutional neural network which is 50 layers deep. All weights used were from Imagenet and the feature extraction was done by removing the last dense layers.

VGG19

VGG-19 is a 19-layer convolutional neural network type that is also a sort of pretrained model. More than a million photos from the ImageNet collection served as the training data for this model network.

In order to lessen model overfitting, the Overfitting Dropout layer was addressed in both the VGG19 and Resnet50 models. Each hidden neuron's output is set to zero with a probability of 0.5 as part of the dropout's operation. On applying a Dropout layer to the input vector, certain features are eliminated; however, if hidden layer is applied some hidden neurons are eliminated. In order to decrease the likelihood of the model being overfit, data augmentation was also used.

METHODOLOGY

The goal of this project is to construct an AI network that can independently process each pixel value after being fed the input data for a specific X-Ray image. The neural network's nodes and layers are then multiplied by the sum of all the afore mentioned operations. There are suddenly millions of operations. Resolve can be applied to certain tasks to improve performance. The goal is to create a deep learning model that can analyze chest X-ray pictures to determine if a patient has pneumonia or not. The model needs to be exceedingly accurate because lives of people are at stake. There are allegations that in the past, when doctors ordered tests or had X-rays taken, they reported a false positive or false negative result (Type 1 or Type 2 error), which was a factor in the patients' poor health. These technologies can therefore help the medical fields by decreasing these errors and saving lives. X-rays are used by doctors to find chest-related issues.

It is a less expensive option than a CT or MRI scan. Thanks to advances in technology, diagnosing infections by taking chest X-rays is now quick and accurate, making the process of finding pneumonia uncomplicated. Only chest X-rays can identify pneumonia, which claims the lives of over 50,000 individuals annually. If there is pneumonia present or not, it is determined by the input, which is once more a front view chest X-ray image.

It is challenging to tell the difference between an unaffected X-ray from pneumonia and a typical X-ray. The only distinction that a non-medical person would be able to make is that the image of a patient with pneumonia is slightly blurrier than the image of a healthy one. This information alone cannot be used to determine the goal value. An X-Ray scan alone may not be enough for a doctor to make a prediction.

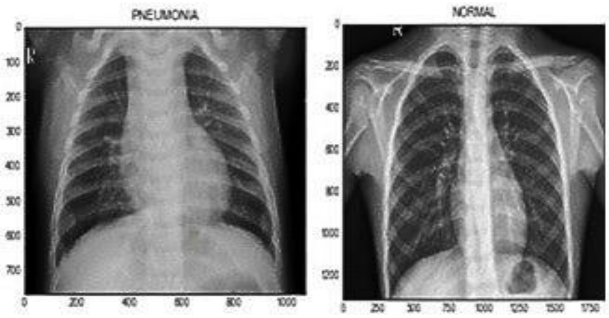


Figure 2: Images of Normal & Pneumonia Effected

Dataset

Kaggle was used to download the pneumonia data set. X-rays images were used to feed the network. Rescaling the images and reduce its pixel size to 200*200 was aimed in the proposed work. It consists of a total image of 5232 belonging to 3 classes (bacterial, normal and viral pneumonia). In which 4744 are used for training and 622 are used for testing purposes. Google colab was used for training in proposed model. The first step was the pre-processing of every image then performing the necessary data augmentation and at last training of the model using different models.

Table 1 Data for training the algorithm.

Parameters	Training Set
Bacterial	2050
Normal	1349
Viral	1345

Table 2 Data for testing the algorithm.

Parameters	Training Set
Bacterial	242
Normal	232
Viral	148

Pre-Processing

It is the foremost step and one of the most vital step to resize all the input images. It refers to the modification of raw data before feeding it to proposed algorithm. Thus, resizing all the input images into the scale of 200*200.

Data Augmentation

To address the issues of data availability and imbalance, data augmentation is utilized. Because CNN performs better with large datasets. This work utilize data augmentation to increase the quantity of dataset since less data is analyzed current work. One of the advantage of using this technique is that it avert the data from overfitting i.e. Hence, here no need to worry about the overfitting of proposed model.

Data Augmentation setting can be done by using the table 3

Table 3 Data Augmentation algorithms.

Parameters	Values Range
Rescale	1/255
Random Zoom	0.2
Random Flip	True
Random Rotation	10

Activation Functions

They are employed to learn and approximate any complex and continuous variable-to-variable association in networks. The network gains nonlinearity as a result. The ReLU, Soft-Max, and tan H are some of the activation functions that are most frequently utilised. By creating a weighted sum and adding bias to it, the activation function determines whether to activate a neuron. The activation function's goal is to make a neuron's output non-linear. Activities for Activation in Different

Forms:***Linear-Functions***

The final action function of the last layer is nothing more than a linear function of the input from the first layer, regardless of how many levels there are if they are all linear in nature. Equation: The equation for a linear function is the same as the equation for a straight line, i.e.

a) From -inf to inf
b) Applications: The linear activation function is solely used in the output layer.

• Problems: By differentiating a linear function to produce nonlinearity, the function becomes constant, the outcome is no longer dependent on the input "x," and the proposed method does not display any innovative behaviour as a result.

Sigmoid Function

• An "S" shape is used to graph the function.
• A is equal to 1/(1 + e-x).
• It has a non-linear character. The X values range from -2 to 2, whereas the Y values are rather steep.. In other words, tiny changes in x would likewise result in significant changes in the value of Y..
• Using the value range of 0 to 1

A binary classification's output layer, where the result can only be either 0 or 1,frequently uses the sigmoid function. Since the sigmoid function's value only has a range of 0 to 1, it is simple to assume that the output will be 1 if the value is greater than 0.5 and 0 if it is not.

Architecture

AlexNet which came out around 2012 which was improved on the traditional Convolutional neural networks. Another iteration of the VGG model is the VGG19, which has 19 layers total, including 16 convolution layers, 3 fully linked layers, 5 levels of max pooling, and 1 layer of softmax.

There are further VGG variations, such as VGG11 and VGG16. 19.6 billion FLOPs make up VGG19. As a result, we will apply the VGG19 model to this issue. The pre-processing of all the photos was the first procedure utilized on the images, and the next stage was the normalization of the images to prepare the data for the model. To proceed to Data Augmentation to improve performance and have different examples to train datasets. To classify data into three different categories the last layer of both the models was set as false and with this algorithm will classify the categories which great accuracies. Also, it is required to decrease computational power load by adding proposed layer (Dense layer and SoftMax activation function in both the Models). The optimizer used is Adam. The VGG19 algorithm is shown in below table 5 for the reference.

After training our model, next step is to test the accuracy. Both the models had the same data pre-processing and augmentation setting to make a fair comparison between the models. So, accuracy and validation accuracy for the two models were as follows:

In case of ResNet50 accuracy of 96.86% was achieved and for Validation accuracy, val accuracy of 95.4% which achieved which is pretty good.

In case of VGG19 the accuracy of 96.36% was achieved and for Validation accuracy of about 91.91% which is less as compared to Resnet50 was achieved. The relevant Graphs of loss and accuracy has been plotted as follow. The loss of about 1.0288 and validation loss is 0.8884 has been observed.

Results for confusion matrix of the algorithms are shown as below:

Table 4: Output Analysis based on Algorithms.

Model	Accuracy	Validation Accuracy	Loss	Validation Loss
ResNet50	96%	95%	0.3	1.18
VGG19	96%	91%	0.43	1.5

Table 5: VGG19 Algorithms Applied to the Dataset for reference.

Layer (type)	Output shape	Param #
Input_1 (Input Layer)	[(None, 200, 200, 3)]	0
block1_conv1 (conv2D)	[(None, 200, 200, 64)]	1792
block1_conv2 (conv2D)	[(None, 200, 200, 34)]	36928
block1_poo1 (Maxpooling2D)	[(None, 100, 100, 64)]	0
block2_conv1 (conv2D)	[(None, 100, 100, 128)]	73856
block2_conv2 (conv2D)	[(None, 100, 100, 128)]	147584
block2_poo1 (MaxPooling2D)	[(None, 50, 50, 128)]	0
block3_conv1 (conv2D)	[(None, 50, 50, 256)]	295168
block3_conv2 (conv2D)	[(None, 50, 50, 256)]	590080
block3_conv3 (conv2D)	[(None, 50, 50, 256)]	590080
block3_conv4 (conv2D)	[(None, 50, 50, 256)]	590080
block3_poo1 (MaxPooling2D)	[(None, 50, 50, 256)]	0
block4_conv1 (conv2D)	[(None, 25, 25, 512)]	1180160
block4_conv2 (conv2D)	[(None, 25, 25, 512)]	2359808
block4_conv3 (conv2D)	[(None, 25, 25, 512)]	2359808
block4_conv4 (conv2D)	[(None, 25, 25, 512)]	2359808
block4_poo1 (MaxPooling2D)	[(None, 12, 12, 512)]	0
block5_conv1 (conv2D)	[(None, 12, 12, 512)]	2359808
block5_conv2 (conv2D)	[(None, 12, 12, 512)]	2359808
block5_conv3 (conv2D)	[(None, 12, 12, 512)]	2359808
block5_conv4 (conv2D)	[(None, 12, 12, 512)]	2359808
block5_poo1 (MaxPooling2D)	[(None, 6, 6, 512)]	0
flatten (Flatten)	(None, 18432)	0
dense (Dense)	(None, 3)	55299

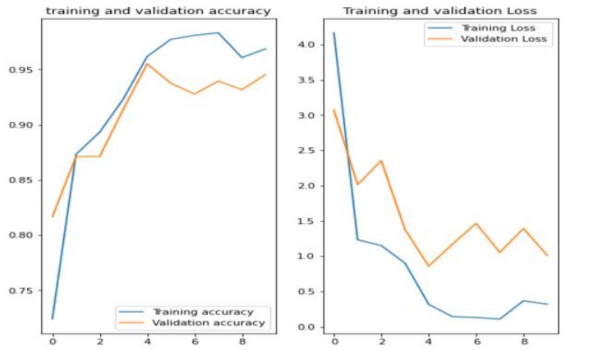


Figure 3: Training & Validation of data loss/Accuracy using VGG19 Algorithms

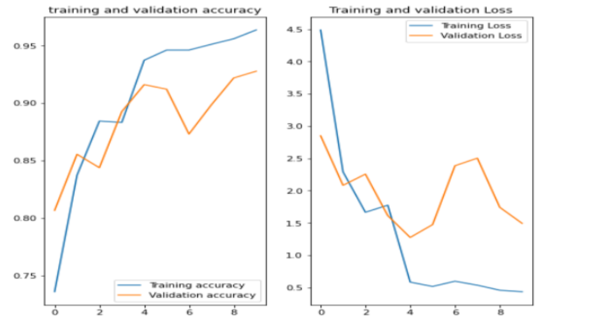


Figure 4 Training & Validation of data loss/Accuracy using Resnet50 Algorithms

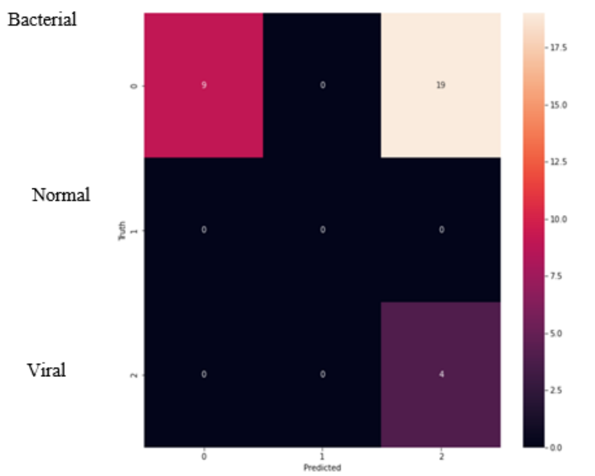
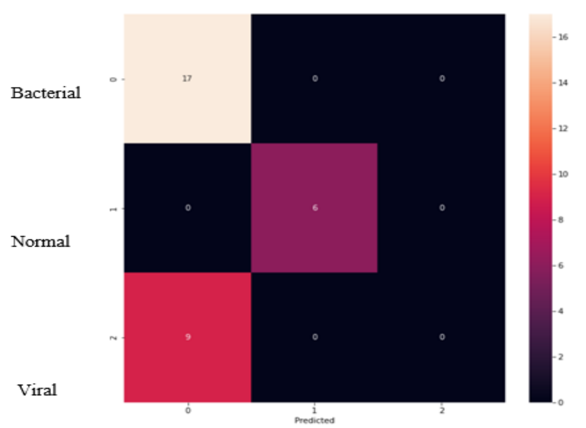


Figure 5: Simulation Results of the Proposed Model using VGG19 Algorithms



Comparison with previous work

Table 6 Comparison

Classes	Topic [Ref. Paper No.]	Methodology	Accuracy	Proposed Outcome
Normal & Pneumonia	Pneumonia Detection Using Transfer Learning [16]	Classification using Vgg16, 19 and Resnet50	91% using Vgg19, 79% using Resnet	
Normal & Pneumonia	Pneumonia Detection in chest X-ray images using CNN [17]	Classification using Vgg16, 19, Resnet50, Inception-v3 & custom models	88% using Vgg19, 77% using Resnet	
Bacterial & Viral Pneumonia	Transfer Learning with Deep Convolutional Neural Network (CNN) [18]	4 different models AlexNet, ResNet18, DenseNet201 and SqueezeNet	93.3% using DenseNet201	91% using Vgg19 95% using Resnet
Bacterial & Viral Pneumonia	Classification of bacterial and viral childhood pneumonia [7]	Deep CNN	80%	

CONCUSION & DISCUSSION

This study investigates how several convolutional neural network models may be used to identify pneumonia using computer vision utilizing deep learning. Every found CNN model is evaluated physically in order to apply the feature extraction and fine-tuning frame-work. The Radiological Society of North America database was used to obtain the dataset of normal chest x-ray images and pneumonia-infected disorders. Our work makes it possible to distinguish between two alternative models that have an accuracy rate of 95% and 91% for detecting pneumonia, Resnet50 and VGG19. The least accurate model, with a 91% accuracy rate, is VGG19. Both models have been successful at identif-ying pneumonia and regular chest x-rays. With the aid of this research, a distinguished method of diagnosing and detecting pneumonia may be useful in the delivery of medical services. Future research must adapt various convolu-tional neural network designs, such as Inception-v3, shuffling Net, and Mobile Net architectures for pneumonia diagnosis, and hyper-parameter optimization should also be taken into account to increase the model's accuracy.

The two separate deep learning models for the identification of pneumonia (ResNet50 and VGG19) are represented in the work that has been presented. Two distinct algorithms were used to classify images into 3 different classes (Bacterial, Normal and Viral Pneumonia). The accuracies of ResNet50 and VGG19 were 95% and 91% respectively which is a more as compared to other works. Among these models it was clear after studying the results and comparing them with recent works that ResNet50 model performed the best (with the accuracy of 95%) when classifying images into 3 different classes as compared to the previous 2 works [16][17] where ResNet50 models achieved the accuracies of 79% and 77% and the 2 output classes there were Normal & Pneumonia. On the other hand our VGG19 model which achieved the accuracy of 91% was almost the same as in [16] (91%) and more as compared to [17] (88%). In short ResNet50 shows promising results to provide highly precise diagnostic results, thus can be used in helping healthcare systems to detect early Pneumonia in patients. The future work can be focused on achieving High Recall and F1 scores in further work since recall is a crucial performance metric for any model because it's crucial to reduce the amount of false negatives.

REFERENCES

R. J. Jose and J. S. Brown. (2016), "Opportunistic bacterial, viral and fungal infections of the lung." Medicine, vol. 44, no. 6, pp. 378-383, doi: 10.1016/j.mpmed.2016.03.015.

Bougias, H., et al. (2019) "Identifying pneumonia in chest X-rays: Comparison between different transfer learning methods." European Congress of Radiology ECR.

Hashmi, Mohammad Farukh, et al. (2020), "Efficient pneumonia detection in chest xray images using deep transfer learning." Diagnostics 10.6: 417.

Labhane, Gaurav, et al. (2020), "Detection of pediatric pneumonia from chest x-ray images using CNN and transfer learning." 3rd International Conference on Emerging Technologies.

Karen Simonyan & Andrew Zisserman, (2015), "Very deep convolution network for large-scale image recognition." Published as a conference paper at ICLR.

S. Rajaraman, S. Candemir, I. Kim, G. Thoma, and S. Antani, (2018), "Visualization and interpretation of convolu-tional neural network predictions in detecting pneumonia in pediatric chest radiographs," Applied Sciences, vol. 8, p. 1715.

X. Gu, L. Pan, H. Liang, and R. Yang, (2018), "Classification of bacterial and viral childhood pneumonia using deep learning in chest radiography," in Proceedings of the 3rd International Conference on Multimedia and Image Processing, 88-93.

Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., & Lungren, M. P. (2017). Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv preprintarXiv:1711.05225.

Cireşan, D. C., Meier, U., Masci, J., Gambardella, L. M., & Schmidhuber, J. (2011). High-performance neural networks for visual object classification. arXiv preprint arXiv:1102.0183.

O'Shea, K., & Nash, R. (2015). An introduction to convolutional neural networks. arXiv preprintarXiv:1511.08458.

Srivastava, N. (2013). Improving neural networks with dropout. University of Toronto, 182, 566.

Rahman, Tawsifur, et al. (2020), "Transfer learning with deep convolutional neural network (CNN) for pneumonia detection using chest X-ray." Applied Sciences 10.9: 3233.

A. Imran. (2019). Training a CNN to detect Pneumonia.

V. Militante, N. V. Dionisio and B. G. Sibbaluca, (2020)," Pneumonia Detection through Adaptive Deep Learning Models of Convolutional Neural Networks," 2020 11th IEEE Control and System Graduate Research Colloquium (ICSGRC), Shah Alam, Malaysia, 2020, pp. 88-93, doi: 10.1109/ICSGRC49013.2020.9232613.

M. F. Hashmi, S. Katiyar, A. G. Keskar, N. D. Bokde, and Z. W.Geem, (2020), "Efficient Pneumonia Detection in Chest Xray Images UsingDeep Transfer Learning," Diagnostics, vol. 10, no. 6, p. 417, Jun. 2020,doi: 10.3390/diagnostics10060417.

Maahi Patel, Ayush Sojitra, Zeel Patel, Mohammed Husain Bohara, (2019), "Pneumonia Detection Using Transfer Learning". Published by International Journal of Engineering Research & Technology (IJERT).

Rachna Jain, Preeti Nagrath, Gaurav Kataria, V. Sirish Kaushik, D. Jude Hemanth, (2015), "Pneumonia Detection in chest X-ray images using Convolutional Neural Networks and Transfer Learning"

Tawsifur Rahman, Muhammad E. H. Chowdhury, Amith Khandakar, Khandaker R.Islam, Khandaker F. Islam, Zaid B. Mahbub, Muhammad A. Kadir, Saad Kashem, (2012)"Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection using Chest X-ray"

eISSN: 1303-5150