

Detection and Classification of Pneumonia Using Deep Learning by the Dense Net-121 Model

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Abstract—A chronic respiratory disease known as pneumonia can be devastating if it is not identified and treated in a timely manner. For successful treatment and better patient outcomes, pneumonia must be identified early and properly classified. Deep learning has recently demonstrated considerable promise in the area of medical imaging and has successfully applied for a few image-based diagnosis tasks, including the identification and classification of pneumonia. Pneumonia is a respiratory illness that produces pleural effusion (a condition in which fluids flood the lungs). COVID-19 is becoming the major cause of the global rise in pneumonia cases. Early detection of this disease provides curative therapy and increases the likelihood of survival. CXR (Chest X-ray) imaging is a common method of detecting and diagnosing pneumonia. Examining chest X-rays is a difficult undertaking that often results in variances and inaccuracies. In this study, we created an automatic pneumonia diagnosis method, also known as a CAD (Computer-Aided Diagnosis), which may significantly reduce the time and cost of collecting CXR imaging data. This paper uses deep learning which has the potential to revolutionize in the area of medical imaging and has shown promising results in the detection and classification of pneumonia. Further research and development in this area is needed to improve the accuracy and reliability of these models and make them more accessible to healthcare providers. These models can provide fast and accurate results, with high sensitivity and specificity in identifying pneumonia in chest X-rays.

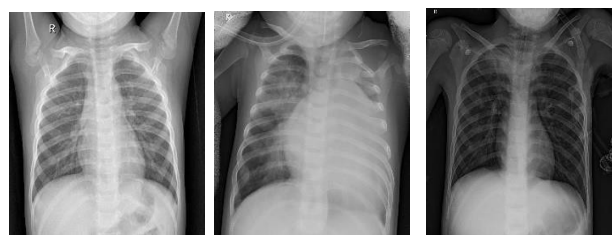
Keywords—Pneumonia, Medical Imaging, Deep Learning, Computer-Aided Diagnosis, CXR Imaging, Pleural Effusion, COVID-19, Early Detection, Accuracy, Reliability, Sensitivity, Specificity.

I. INTRODUCTION

Pneumonia is a serious respiratory illness that can cause significant harm and even death, if not detected and treated promptly. Early and accurate diagnosis of pneumonia is crucial for effective treatment and improved outcomes for patients [3]. However, traditional methods of diagnosing pneumonia, such as chest X-rays and physical exams, can be time-consuming and unreliable. To address this challenge, researchers are turning to deep learning techniques, which have shown promising results in the field of medical imaging. One such deep learning approach is the use of convolutional neural networks (CNNs),

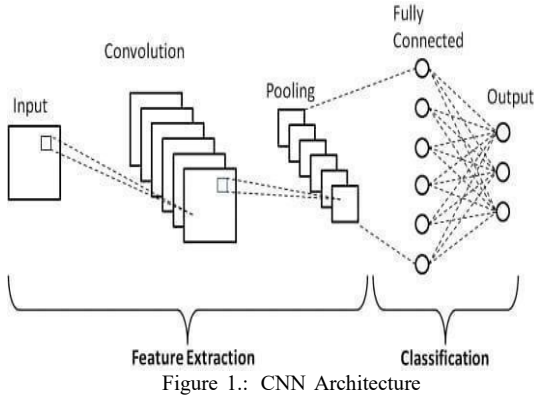
specifically DenseNet-121 model, for pneumonia detection and classification. The DenseNet-121 model is trained on large datasets of chest X-rays, and can analyze medical images to identify patterns and features that are indicative of pneumonia [13]. The main goal of this study is to measure the performance of the DenseNet-121 model in detecting and classifying pneumonia. This prototype will be tested against diverse dataset of chest x-rays images [6].

These results will be compared to traditional methods of diagnosis. The findings of this study will contribute to the development of more accurate and efficient methods for the detection of pneumonia using deep learning methods [9]. Overall, deep learning use for pneumonia detection and classification holds significant potential for improving the accuracy and efficiency of the diagnostic process. This research will provide valuable insights into the capabilities of the DenseNet-121 model and its potential for real-world applications in medical imaging.



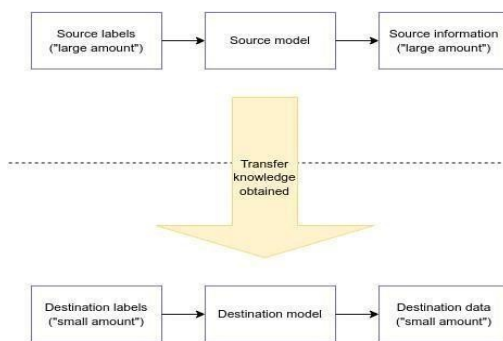
Normal Image Bacterial Image Virus Image Deep Learning: A branch of machine learning called "deep learning" focuses on utilizing artificial neural networks to model complex patterns and relationships in large amounts of data [8]. It uses multiple layers of artificial neurons to extract increasingly complex features from the data, allowing the network to learn and make predictions about new data. DL models, especially Convolutional Neural Networks (CNNs), are widely utilized for various image classification issues. In CNN, the term convolution implies a special kind of linear operation, where two functions are increased to create a third function [5]. This means that two pictures indicated as matrices are multiplied, and their

yield is utilized for the image feature extraction process. CNN models are prepared on massive datasets such as ImageNet, which has millions of pictures regularly utilized for restorative picture classification issues [7]. CNN Architecture Is show in fig.1



A. Transfer Learning

A pre-trained model that was built for a particular task is utilised as the foundation for a new model that is created for yet another task in a process known as transfer learning [10]. Most of the tasks include computer vision and typical language processing. Reusing means using a model that has already been trained on a big dataset to solve a problem using a smaller dataset. The new model incorporates the network weights used in the previous model. Since developing a model for an image from scratch is rare, transfer learning is shared scratch. Examples of models with a transfer learning foundation include ImageNet, AlexNet, and Inception. Transfer Learning Is show in fig.1.2

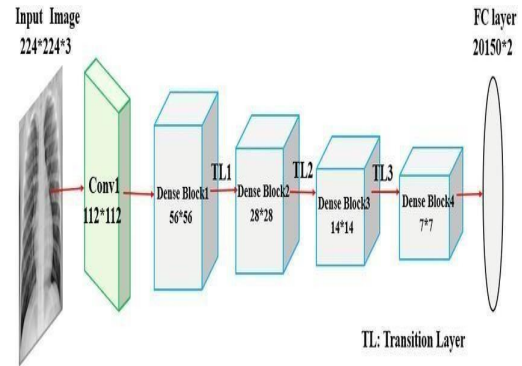


B. DenseNet-121

The term "DenseNet" refers to a densely twisted neural network in which each layer is connected to all previous levels in the deep network [2]. In DenseNet, the layers are connected in a way that, for instance, if a network has n layers, the n th layer entering the internal network is connected to all the levels up to the first outermost layer. The second outer layer, for instance, is similarly connected to every layer in the network up to the n th layer if we take it as an example. A common network architecture that employs deep learning networks to effectively comprehend the intricacy of connections even

at the innermost layer is called DenseNet, which is a multilayer network [6].

As a result, maximum data flow between network tiers is enabled. This is described adequately by employing short connections rather than long connections between network levels. Every layer in the network is fed by feature mappings from prior layers. This is known as feed-forward nature [8]. DenseNet Architecture Is show in fig.1.3



C. Data Preprocessing and Image Augmentation

Data preprocessing: To meet the predetermined input size of the DenseNet-121 architecture, training data pictures are resized to 224 by 224. There must be a 0 and a 1 in each picture pixel. X-ray scans are typically single-channel grayscale images, while DenseNet-121 anticipates a three-channel RGB image. In order to create photos that are compatible with the DenseNet-121 highlight extraction model, this issue is resolved by repeating the primary channel twice [11].

Data Augmentation: It tries to reduce overfitting difficulties by increasing the dimensions of the training data and ensuring that photos with tiny sizes are elevated higher than the other class to balance the different data classes. The Training dataset chest x-ray pictures are subjected to image operations such as rotating, shifting, shearing, and zooming with tiny values to ensure that the images created by such procedures do not differ significantly from the genuine ones. Data augmentation is performed on the dataset by using ImageDataGenerator in Python [12].

II. PROPOSED SYSTEM

Building a model for automatically detecting pneumonia is the aim of this work using the DenseNet-121 model that has already been trained. The DenseNet-121 model takes the key characteristics from pictures used in training. Dense-net 121 is employed because it can more accurately diagnose pneumonia from X-ray images and better represents the lung characteristics. The flatten layer is the very first layer of the model, and the output layer is the last layer. Both layers include an activation function called softmax and the necessary values for the number of hidden dense layers and their corresponding neurons. Additionally, figuring out the model training learning rate is crucial for

greater accuracy [14].

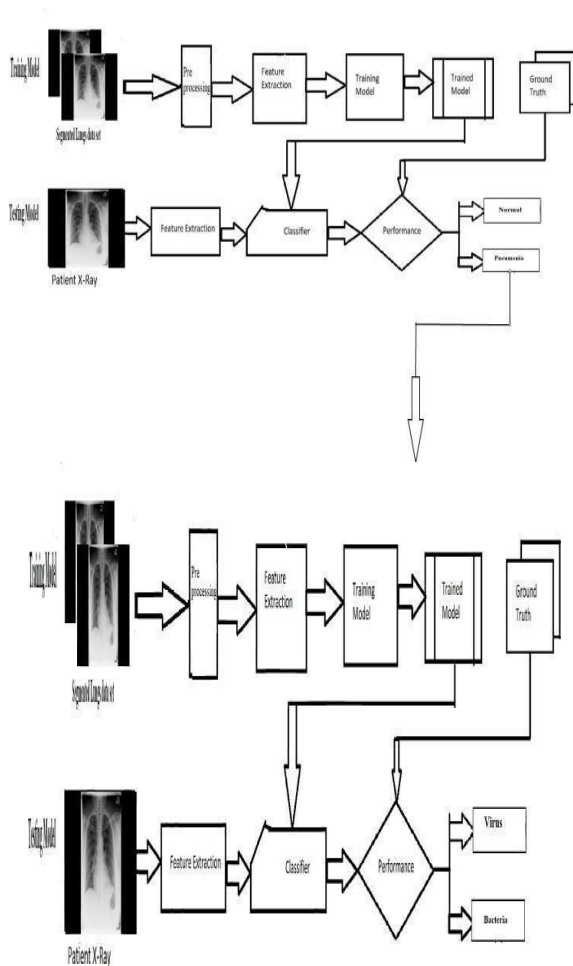


Figure 2: Proposed System Architecture

A. Primarmary Classification (Classifier-I):

According to our model, we categorised the CXR pictures into the normal class and the pneumonia class using DenseNet-121 as a basis model (binary classification) [4]. After the input layer has been

flattened, the output layer is followed by a hidden layer that contains two neurons with the softmax activation function and 128 neurons with the relu activation function. Zooming, flipping, shearing, and rescaling parameters were added to the training set dataset[9].

TABLE 2.1 DATA SPLITTING INTO NORMAL AND PNEUMONIA IMAGES

of the Class	Trainin gdataset	Testin g dataset	Total
Normal	1279	302	1581
Pneumonia	3877	398	4275
Total	5156	700	5856

The classifier 1.h5 extension is used to store the learned model file [1]. When pneumonia is found at this classification step, the second classifier is brought into play. Accuracy graph for classifier-1 and LossGraph for classifier-1 is show in fig.2.1 a,b

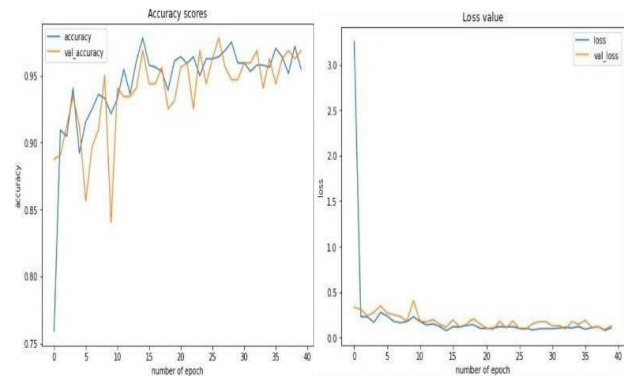


Figure 2.1: a) Accuracy graph for classifier-1 b) LossGraph for classifier-1

B. Secondary Classification (Classifier-II):

The second classifier enters the picture when pneumonia is found in the first classification. In order to determine whether the CXR pictures belong to the viral class or the bacterial class, we categorised them using the CNN model (4 convolutional layers, 2 max pool layers) (binary classification). After the flattened input layer, there are two hidden layers: the first has 100 neurons and a relu activation function, while the second has 50 neurons and a relu activation function [15]. Two neurons serve as the output layer at the end and have a softmax activation function. Added parameters for the training set dataset included zooming, flipping the dataset horizontally, shearing, and rescaling. The classifier 2.h5 extension is used to store the trained model file.

Name of the Class	Training dataset	Testing dataset	Total
Bacteria	2538	243	2781
Virus	1342	150	1492
Total	3880	393	4273

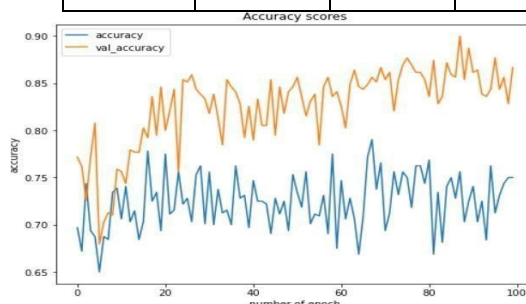


Figure 2.2: (a) Accuracy graph for classifier-2

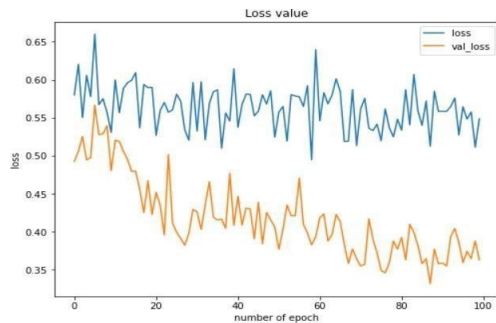


Figure 2.2: b) Loss graph for classifier-2

III. METRICS FOR MODEL EVALUATION

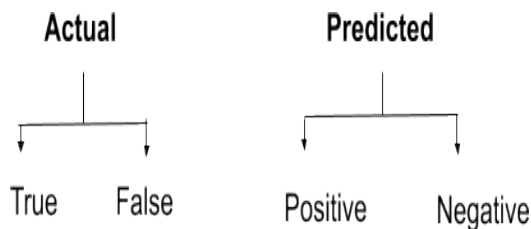
To determine how well a model is doing, it is assessed against a set of benchmarks and metrics. Following data training, we must determine model metrics such as accuracy rate, recall value, precision value, and F1- score. Before learning the meanings of these measures, it is necessary to understand a few words. They are :

*True Positive (TP) - A true positive is a prediction made by the model that an instance is positive (belongs to the positive class), and the instance is positive.

*True Negative (TN) - A true negative is a prediction made by the model that an instance is negative (does not belong to the positive class), and the instance is negative.

*False Positive (FP) - A false positive is a prediction made by the model that an instance is positive (belongs to the positive class), but the instance is negative.

*False Negative (FN) - A false negative is a prediction made by the model that an instance is negative (does not belong to the positive class), but the instance is positive.



The 4 metrics involved in evaluating the model are:

A. *Accuracy* - Measures the percentage of total number of correct predictions

Accuracy = $(\text{True Positives} + \text{True Negatives}) / \text{Total instances}$

where Total instances are the total of True Positives, True Negatives, False Positives, and False Negatives, and True Positives (TP) are instances that are correctly categorised as positive, True Negatives (TN) are instances that are correctly classed as negative.

B. *Precision* - Measures the percentage of actual positive predictions out of the positive predictions.

Precision = $\text{True Positives} / (\text{True Positives} + \text{False Positives})$

C. *Recall (Sensitivity)* - Evaluates the percentage of total number of positive predictions.

Recall = $\text{True Positives} / (\text{True Positives} + \text{False Negatives})$

D. *F1-score* - Measures an equilibrium between precision and recall values to compare.

F1-score = $2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$

TABLE 3(A): REPORT OF CLASSIFICATION FOR CLASSIFIER -1

	Precision	Recall	F1-score	Support
Normal	0.95	0.95	0.96	300
Pneumonia	0.97	0.96	0.97	400
Accuracy			0.96	700
Macro avg	0.96	0.96	0.96	700
Weighted avg	0.96	0.96	0.96	700

TABLE 3(B): REPORT OF CLASSIFICATION FOR CLASSIFIER -2

	Precision	Recall	F1-score	Support
Bacteria	0.86	0.94	0.90	242
Virus	0.88	0.75	0.81	148
Accuracy			0.87	390
Macro avg	0.87	0.84	0.85	390
Weighted avg	0.87	0.87	0.86	390

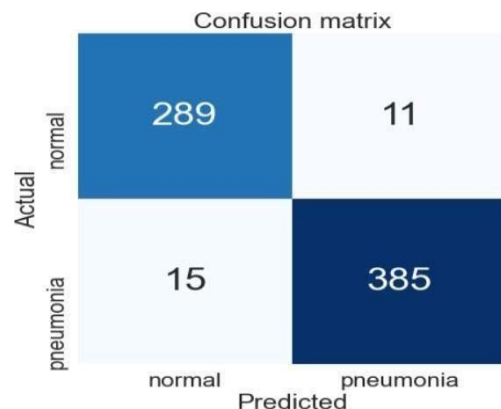


Figure 3. a) Confusion matrix for classifier - 1

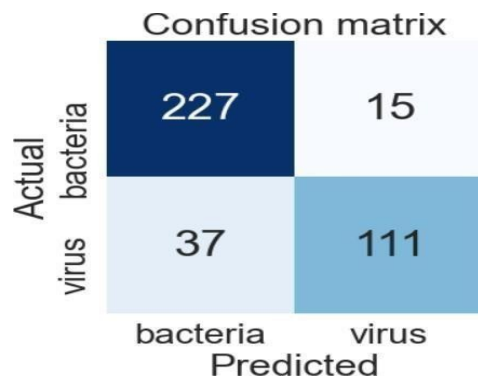


Figure 3.b) Confusion matrix for classifier - 2

Confusion matrix for classifier – 1 and Confusion matrix for classifier – 2 is show in fig.3.a, b

TABLE 3(C): COMPARISON OF CURRENT WORK WITH PREVIOUSWORKS FOR CLASSIFIER-1

Related Work	Model used	No. of images	Accuracy(%)
Luka Racic [1] (2021)	CNN	5856	90
Dejun Zhang [3](2021)	VGG16	5856	96.07
shangjie yao [4](2021)	Faster R-CNN	5856	95
Saraiva et al. [6] (2019)	CNN	5840	94.40
Kaushik, V. & Nayyar, Anand & Kataria, Gaurav & Jain, Rachna. [5](2020)	CNN	5856	92.31
Proposed work (2022)	DenseNet-121	5856	96.7

IV. CONCLUSION

A chronic lung infection that affects and damages the lungs called pneumonia. A curative treatment is aided by early disease identification and detection. Although X-ray imaging is a practical method of diagnosing pneumonia, viewing such pictures often makes it more difficult to identify the illness. Even after finding pneumonic lungs, it is frequently difficult to determine the disease's underlying origin, i.e., to categorise it as viral or bacterial. Using an automated system, this effort aims to shorten the time needed for illness diagnosis and categorization while improving accuracy. The system receives an input x-ray picture, analyses it, and assigns it a classification. When pneumonia is found, the aetiology of the illness is further categorised. Densenet-121 and the CNN models serve as the foundation for this model. The first classification achieved an accuracy of 96%, while the second classification achieved an accuracy of 87%. To the benefit of patients and medical professionals, this work may be expanded upon and applied in every diagnostic facility.

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