VOLUME - 11, ISSUE - 05, MAY - 2022 • PRINT ISSN No. 2277 - 8160 • DOI : 10.36106/gjra

Original Research Paper | Machine Learning

PNEUMONIA ANALYSIS, DETECTION, AND CLASSIFICATION THROUGH VARIOUS CLASSIFIERS

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ABSTRACT Pneumonia kills about a million children and adults each year and affects 7% of the world's population. Chest X-rays are mainly used to diagnose pneumonia. However, even for a trained radiologist, examining chest X-rays with the naked eye is challenging. There is a need to improve diagnostic accuracy with an automated system. This article proposes an efficient classification model for pneumonia detection, trained on digital chest radiographs. It would help the radiologist in their decision-making process. An original approach that depends on a weighted classifier is proposed that optimally integrates the weighted predictions of the most advanced deep learning model such as ResNet, Xception, Inception, DenseNet, and MobileNet. This deep learning approach is a supervised learning approach in which the model predicts the results based on the quality and availability of the dataset. In this investigation, a promising result has been obtained for the MobileNet classifier with an accuracy of 92%. More accuracy and classification techniques can be improved by using more datasets.

KEYWORDS : Pneumonia, CNN, X-rays, WHO, Artificial Intelligence.

I. INTRODUCTION

The threat of pneumonia is tremendous for many developing countries where billions face fuel poverty and depend on polluting kinds of energy. WHO estimates that more than 4 million premature deaths from diseases related to household air pollution, including pneumonia, occur every year [1]. More than 150 million people are infected with pneumonia every year, especially children under the age of 5 [2]. The problem can be further exacerbated in such regions because of the dearth of clinical assets and staff, for instance, with inside the 57 international locations in Africa an opening of 2. There are 3 million medical doctors and nurses [3],[4]. For those populations correct and speedy prognosis method is everything. You can ensure timely access to treatment, saving much-wished money and time for the ones already in poverty.

Many tests are available to diagnose pneumonia, including chest X-ray (CXR), chest MRI, and needle biopsy of the lungs [5]. The cheap and most widely used of these methods is CXR, which makes a crucial contribution to medical care and epidemiological studies [6],[8]. The X-ray approach is more optimal than the CT approach because CT imaging takes a longer time than X-ray. Also, CT scans require wonderful scanners, and those styles of scanners might not available in lots of underdeveloped countries. In many areas of the world, there may be the trouble of a scarcity of scientific groups of workers and radiologists, however, they play a critical function in the detection and prediction of pneumonia [9], [10]. Nowadays, the famous technique to diagnose pneumonia sickness is the use of Artificial Intelligence (AI) primarily depends totally on computers, cell devices, cloud servers, and edges [11],[12].

One of the widely used medical techniques to identify the disease is a chest X-ray. When the beam of electrons, called X-ray photons, penetrates the body tissue, an image is formed on the photographic film. When examining chest X-rays for pneumonia identification, the doctors and radiologists look for white spots in the lungs called infiltrates that identify infection. The limited color scheme of X-rays, consisting of black and white tones, causes inconvenience. when trying to determine whether or not there is an infected area in the lungs. However, these blurred patterns would also be seen in tuberculous pneumonia and severe cases of bronchitis.

For conclusive diagnosis, investigations along with whole blood count (CBC), Sputum test, Chest computed tomography (CT) scan, etc. can be needed. Therefore, we're simply trying to hit upon the opportunity of pneumonia from Chest X-rays, seeking out a cloudy place. Conclusive detection will rely on pathological tests.

II. MATERIALS AND METHODS

The details of the experiment and the assessment step to check the effectiveness of the proposed model are shown. Our experiment is primarily based totally on the chest X-ray dataset. For coding, we used Python version 3.8 with open CV libraries. We implement the open-source Keras deep learning framework with the TensorFlow backend to construct and train the Convolutional Neural Network model. The experiments are performed on a standard system with an Intel Core i5 9300H @ 4.10 GHz processor (CPU), a GTX 1650 graphics card (GPU), and 8 GB DDR4 RAM.

2.1 Dataset

The dataset used in this work has been collected from

Kaggle.com, Get Life Hospital Amravati, and Harshivanand Hospital, Varanasi. The dataset consists of 5856 chest X-rays with resolutions ranging from 400p to 2000p. Out of 5,856 chest X-rays, 4,270 are for pneumonia and 1,580 are for healthy subjects (Table 1). Pneumonia is caused by viral and bacterial infections. However, the dataset used in this examine does now no longer encompasses viral and bacterial co-contamination cases. This data set was segmented into training and test sets.

Table 1: Complete detail of the Dataset

Type of subject	Number of X-ray images	Source
Normal	1580	Kaggle.com
Pneumonia	4270	Get Life Hospital + Harshivanand Hospital
Total	5856	Get Life Hospital + Harshivanan Hospital + Kaggle

Table 2 shows the training and test set segmentation, the variety of the train (the usage of augmentation), and test images for extraordinary assessment experiments. Four extraordinary algorithms had been trained on the usage of the training dataset which was evaluated in the test dataset. The figures underneath display samples for regular and Pneumonia chest X-ray images from the dataset.

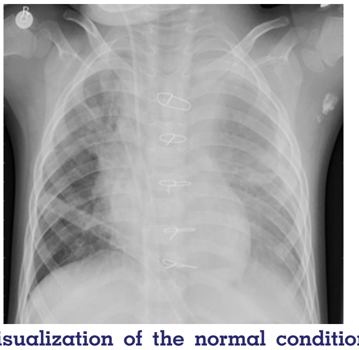

Figure 1: Visualization of the normal condition from the training dataset

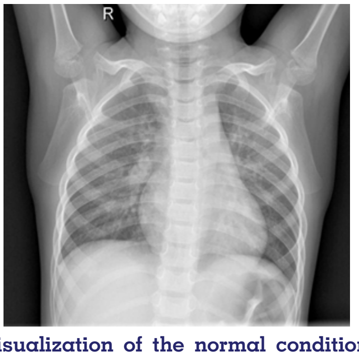

Figure 2: Visualization of the normal condition from the validation dataset

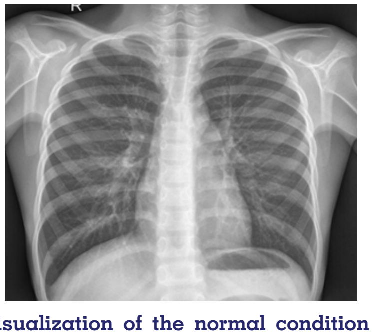

Figure 3: Visualization of the normal condition from the testing dataset

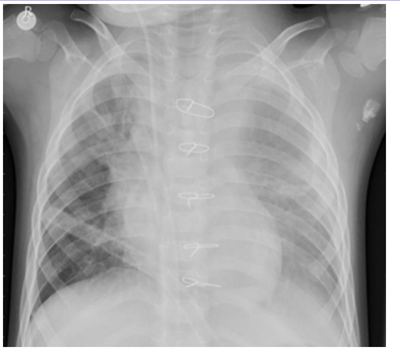

Figure 4: Visualization of Pneumonia condition from the training dataset

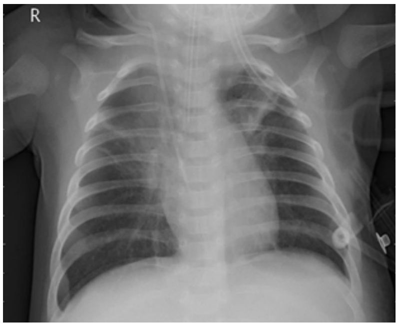

Figure 5: Visualization of Pneumonia condition from the testing dataset

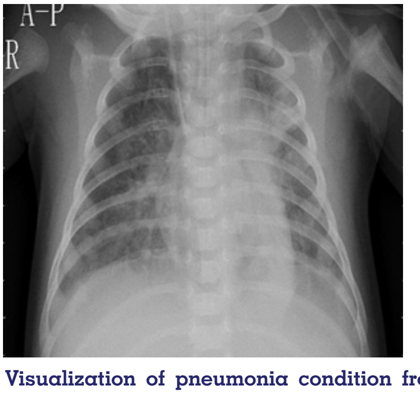

Figure 6: Visualization of pneumonia condition from the validation dataset

Table 2: Details of Training and Test set

Types	Training Set		Testing Set	Validation
Normal and Pneumonia	Normal	1341	234	8
	Pneumonia	3875	390	8

2.2 Data Pre-processing

A local library consists of 5,856 X-ray images for pre-processing of the data. Using this local library, it automatically detects categories within the dataset and adjusts the image size even if we don't specify the image size. The default image size is 50x50. The pickle object is used to reduce the time it takes to load the data.

2.3 Data Augmentation

CNNs produce an efficient result with a large number of datasets. However, the scale of the operating database isn't always very huge. There is the usual place trend in training deep learning algorithms to make the relatively smaller dataset right into a large one using data augmentation techniques. It has been pronounced that data augmentation can ameliorate the classification accuracy of deep learning algorithms. The overall performance of the deep learning models may be ameliorated through augmenting the prevailing data in preference to gathering new data. Some of the deep learning frameworks have inbuilt data augmentation techniques. however, in this study, the authors have applied Keras ImageDataGenerator to generate new training sets.

Keras ImageDataGenerator function is an image enhancement technique for applying different alterations to the authentic images, ensuing in multiple converted copies of the identical image. However, each copy differs in certain aspects depending on augmentation techniques such as scrolling, rotating, flipping, etc. These image enhancement techniques not only extend the scale of the dataset but additionally contain a diploma of variant withinside the dataset that permits the version to higher technique invisible statistics and generalize. Also, the version turns into extra effective while trained with new, slightly modified images. So, with only some traces of code, one could immediately create a huge corpus of comparable images while not having to fear approximately amassing new images, which isn't beneficial in a real global scenario.

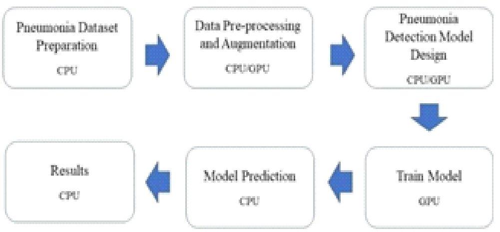

Figure 7: Flow Chart of the Proposed Model

2.4 Convolutional Neural Networks (CNNs)

CNNs are beneficial equipment in computer vision to categorize and understand input objects from 2D and 3-D images [13]. The conventional architecture of the CNN model generally includes a few couples of convolutions and pooling layers. Some techniques which include batch normalization [14], dropout [15], and ResNet block [16] were implemented to enhance the accuracy and performance of deep CNN models.

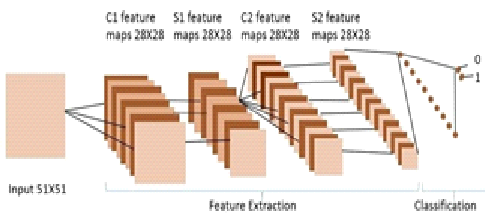

Figure 8: Architecture of two major layers [8]

The classifier is located at the next end of the proposed Convolutional Neural Network (CNN) model. A classifier wishes character features (vectors) to carry out computations like some other classifier. Therefore, the output of the feature extractor (a part of CNN) is transformed right into a 1D function vector for the classifier method called flattening, in which the output of the convolution operation is flattened to provide an extended feature vector for the dense layer to apply in its very last classification process. The classification layer carries an oblate layer, dense layers of length 80 and 1, respectively, at RELU among the 2 densest layers, and a sigmoid activation feature that plays the classification tasks. The mathematical expression for RELU and sigmoid in which we get the theoretical value is

RELU: $y = \max(0, x)$ (2)

Sigmoid: $S(x) = 1/1+e\text{-}x$ (3)

The visual representation of RELU and Sigmoid functions are given below. An extensive type of sigmoid functions consisting of the logistic and hyperbolic tangent capabilities had been used because of the activation function.

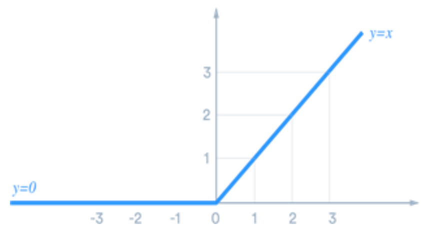

Figure 9: Visualization of RELU Curve [23]

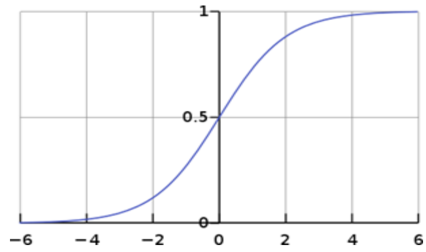

Figure 10: The Logistic Curve of Sigmoid function [24]

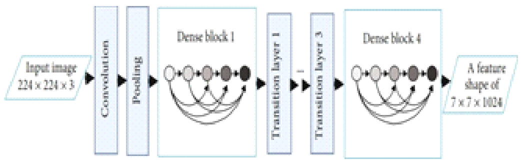

Figure 11: The architecture of the DenseNet Model [5]

RESULTS

Attempts have been made to assess classification performance using metrics such as precision and loss. The classification accuracy is the overall performance assessment measure. Accuracy represents how properly the classifier does in predicting times primarily based totally on the training data.

Accuracy: It is the ratio of the number of real anticipated instance each positive and negative to the total no. of instances.

Accuracy (%) = ((TruePositive + TrueNegative) / Total no. of instances) * 100

These terminologies are explained below:
1. True Positive: Number of predicted positive and actual positive instances.
2. True negative: No. to instances predicted positive but are actually negative.
3. Total Instances: The sum of all instances classified by the classifier.

Table 4: Accuracy of Proposed Model

Dataset	Accuracy of Proposed Model
Training	94.37%
Test	91.34%
Validation	92.11%

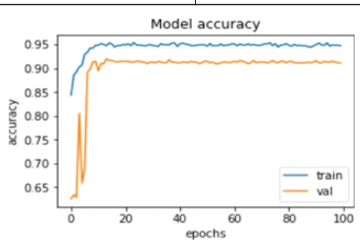

Figure 11: Visualization of Model Accuracy

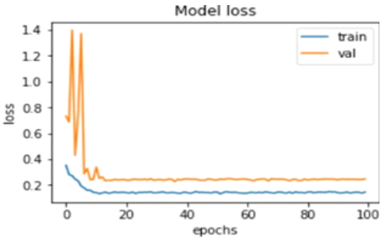

Figure 11: Visualization of Model Loss

IV. CONCLUSION AND DISCUSSION

We proposed a model that classifies positive and negative pneumonia data from a group of radiographs. Our model is constructed from scratch, which distinguishes it from different strategies that depend closely on the transfer learning approach. And we enforce the created model in software that can work on Android and IOS. In the future, this work could be extended to come across and classify X-ray images with COVID19 and pneumonia has been a big problem lately and our next approach will address this issue.

ACKNOWLEDGMENT

The authors sincerely thank Dr. Prajakta Ingole, Get Life Hospital; Amravati, Maharashtra, INDIA for all types of databases provided time to time that contributed to this research work.

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