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Article · May 2022

DOI: 10.48175/IJARSCT-3851

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
Impact Factor: 6.252
Volume 2, Issue 3, May 2022

Pneumonia Detection and Classification using CNN and VGG16

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Abstract: *Pneumonia, an infectious disease caused by a bacterium in the lungs' alveoli, is frequently the result of pollution. A lung infection causes pus to build up in the affected tissue. Professionals conduct bodily examinations and diagnose their patients using a chest X-ray, ultrasound, or lung biopsy to determine if they have certain conditions. Misdiagnosis, incorrect treatment, and failure to recognize the disease will result in a patient's inability to lead a normal life. Deep learning's advancement helps specialists make better decisions when diagnosing patients with certain diseases. The research provides a flexible and efficient deep learning technique that uses the CNN model to predict and detect a patient who is unaffected. Using a chest X-ray photograph, the study applies a flexible and effective deep learning technique of using the CNN model in predicting and detecting a patient unaffected and affected by the illness. To demonstrate the overall performance of the CNN model being trained, the researchers used an amassed dataset of 20,000 photographs and a 224x224 photograph decision with 32 batch lengths. At some point throughout the total performance training, the trained version produced a 95 percent accuracy charge. The research study may detect and predict COVID-19, bacterial, and viral pneumonia illnesses based solely on chest X-ray photographs, according to the results of the testing.*

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

I. Introduction

Pneumonia is an inflammation of the lung parenchyma caused by pathogenic bacteria, physical and chemical factors, immunologic injury, and various medications.

There are several common pneumonia classification methods: (1) Pneumonia is classed as infectious or non-infectious based solely on unique pathogeneses, with infectious pneumonia being the more common. Immune-associated pneumonia, aspiration pneumonia induced by physical and chemical factors, and radiation pneumonia, among other things, are all types of infectious pneumonia. Immune-associated pneumonia, aspiration pneumonia produced by physical and chemical factors, and radiation pneumonia are all examples of non-infectious pneumonia. (2) Pneumonia is divided into three types: CAP (community-acquired pneumonia), HAP (hospital-acquired pneumonia), and VAP (ventilator-related pneumonia), with CAP accounting for the majority of occurrences. as a result of the wide range of disorders,

HAP makes it easier to develop resistance to a variety of antibiotics, making treatment more challenging. Every year, more than 800,000 children under the age of five die from pneumonia. over 2200 people die. More than 1400 children per 100,000 become affected by pneumonia. Pulmonary infections, such as pneumonia, were the second greatest reason for death in 2013, according to the Global Burden of Disease Study. The pneumococcal disease has inflamed approximately 35 percent of patients in European hospitals, and 27.3 percent of patients worldwide. According to a recent report from John Hopkins Bloomberg College of Public Health, India had the highest rate of pneumonia mortality, with nearly 2.97 lac pneumonia combined diarrhea mortality among children under the age of five in 2015. similarly, Pneumonia was the leading cause of death among children under the age of five years old in 2015. Furthermore, pneumonia's death rate is inversely proportional to its age, and pneumonia's superiority rises substantially with age, especially in humans older than sixty-five. The huge range of baby deaths via pneumonia alarms scientists international to recommend extra effective and acute strategies to stumble on pneumonia. With the era growing, greater and extra measures are advanced, where radiology-based treatments are the most popular and effective. Chest X-ray imaging, computed tomography (CT), and magnetic resonance imaging (MRI) are all diagnostic radiological techniques for pulmonary disease, with chest X-ray scanning being the most efficient and cost-effective because it is far more accessible and portable in hospitals, and it exposes sick people to lower doses of radioactivity. However, even for multiple skilled and experienced medical physicians, analysing pneumonia using X-ray snapshots remains a difficult task because X-ray images contain comparable area statistics for unique ailments, such as lung cancer. As a result, diagnosing pneumonia with conventional procedures is time-consuming and energy-intensive, and it is impossible to diagnose whether or not a patient has pneumonia in a uniform manner. As a consequence, in this study, we propose using a Convolutional Neural Network to autonomously diagnosis pneumonia using X-ray pictures, with an accuracy of 96.07 percent and an AUC of 0.9911. The remaining sections of this work are organised as follows. The literature's perspectives on medical picture processing processes are discussed in the second section. In recent times, section three has described a rapid way of Convolutional Neural Networks (CNN) architecture. The final segment included an outline of Machine Learning and Deep Learning's history. The material employed in this investigation, our proposed techniques, and the training method are all depicted in Section 4. The trials and their outcomes are presented in section 5. This observer's belief is described in section 6.

II. Related Works

[1]There are several obstacles in creating a sustainable version to identify COVID-19 from X-ray pictures. First and foremost, there are only a limited quantity of photos available. The pandemic has only been spreading for a few months, that there have not been enough datasets collected and published for experts' use. Second, there may be a pressing need for scientific researchers to develop a smart gadget for such rapid identification and deep understanding of viral infections using breast X-ray images, which can show the severity of the problem to the human body. After evaluating the already existing technology and the challenging scenarios we are facing, it has been determined that approach transfer is feasible and realistic for this research challenge. This method involves training deep neural networks on photos of pneumonia including infection in one or both lungs, which could be caused by bacteria, infections, or fungus. The illness produces irritation in the alveoli, that are small air sacs in the lungs. The respiratory system fill with liquid or pus, making breathing difficult. The process utilizes transfer learning on well-studied deep learning methods to identify the type of virus, validates the designs on a wide range of data sets, and then transfers the models and insights learned in training and validation to a new data set in a similar region, that, in this case, is a new infectious fast-growing illness. The coronavirus, also known as COVID-19, is a type of virus. The suggested method addresses a difficult challenge in deep learning: how to build a reliable model based on a limited data set that has not been thoroughly analysed and contains unidentified characteristics.

[2]Deep CNNs indeed acquire higher performance with the use of a huge dataset as compared to a smaller one. Granting there is an enormous range of infected COVID-19 patients globally, however, the variety of publicly to be had chest X-ray photos online is insignificant and dispersed. For this reason, the authors of this work have defined a reasonably huge dataset of COVID-19 infected chest X-ray images even though normal and pneumonia photographs are right away on hand publicly and applied in this study.

[3]Using a chest X-ray image, the observations apply flexible and powerful deep learning methodologies, including the employment of six CNN models to predict and identifying whether the patient is untouched or impacted by the condition. To monitor the accuracy of each version getting learned, GoogLeNet, LeNet, VGG-16, AlexNet, StridedNet, and ResNet-50 models using a dataset of 28,000 images and a 224x224 decision with 32 and sixty-four batch sizes are used. The study also uses Adam as an optimizer, giving all of the models an adjusted 1e-four learning rate and a 500-epoch. During the development of models, both GoogLeNet and LeNet received a 98% accuracy rate, VGGNet-16 received a 97% accuracy rate, AlexNet and StridedNet models received a 96% average accuracy, and the ResNet-50 model received an 80% accuracy rate. For total performance training, GoogleNet and LeNet fashions have the highest average accuracy. The six models identified were possible to perceive and predict a pneumonia illness, which included a normal chest X-ray.

[4]In this paper author classify the three varieties of X-rays, image writer used the ensemble method at some stage in prediction, each picture is surpassed through the type layer where they checked whether an image is COVID-19, pneumonia, or ordinary.

[5]The X-rays dataset is separated into training and test subsets in the first phase of the statistical preprocessing level. Character X-ray pictures are also normalised at this level. For a strong version development, data augmentation of training

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

Impact Factor: 6.252

Volume 2, Issue 3, May 2022

photos was completed. The second degree is the age of a version that divides x-rays into two categories (consolidation and non-consolidation). The use of an okay-fold cross-validation strategy (where okay is the amount of folds) was proven by the correctness of this model. Finally, the deployment of the explainable AI strategy that we chose to improve the comprehensibility of our Machine is the final stage. The arrival of the heatmap. We use one-of-a-kind ways to assess the quality of our Machine: 1) generating the heatmap using the simplest version, and 2) generating the heatmap with an ensemble of styles with the same structure but educated with one-of-a-kind record folds. The second technique allows us to compute an uncertainty level (provided by the same old deviation) for each pixel, allowing us to assess the heatmap's robustness.

[6]The author recommends a current technique based on an ensemble of RetinaNet and masks R-CNN in this paper. Pneumonia regions are known by their size and ratio (Figs. 3 and 4), with a mean top of 304 pixels (29.6% of the photograph peak) and a median width of 219 pixels (21.three percent of picture width). Pneumonia appears in a very small area of a chest x-ray, making it a difficult assignment for modern item detectors. Because FPN provides multi-scale feature maps with higher first-rate statistics than the typical feature pyramid, we employed it as the backbone of both approaches to solve this problem. As shown in Fig. 1, the FPN structure blends low-resolution, i.e. linguistically having in - depth, with enhanced capacities. i.e. semantically weak functions, through a top-down pathway and lateral connections. In comparison to the primary stacked convolutional layers, we employed residual networks as a base spine version because they reduced the effect of the degrading hassle and allowed us to develop deeper designs.

III. Background

Machine learning (ML) algorithms have steadily gained the interest of researchers over the last few years. This type of method can make full use of the massive ability to create computer calculators in image processing with pre-determined algorithm stages. Traditional machine learning methods for dividing jobs, on the other hand, necessitate the use of manual design algorithms or the manual setting of output layers to separate images. In response to the aforementioned situation, LeCun et al. [7]offered a CNN approach, which can automatically extract features with the use of constantly stacking features and exit that the included photos may not be in any class. The shallow networks are very deep and concentrate on the image's low-level features. CNN the model increasingly exposes advanced features as the number of network layers increases. CNN learns the distinctions between different images by combining and evaluating these priority features, and it uses a back-propagation technique to update and record learned parameters. CNN's concept is to use a specific convolution kernel to filter a prior picture or map component to build the next layer map element, as well as merge functions like merging functions to minimise feature map scale and mitigation to count. The created component is then given the non-line activation function.

A mapping to improve the model's simulation capabilities The most common integration tasks include mid and high integration. The plural of integration denotes that the element sent to the integration layer is split into many regions, with each sub-region having a different size in terms of horizontal and vertical steps. The sole distinction between high and medium integration is a lower region where the aggregation rate yields the average of each sub-region. ReLU (Rectified Linear Units) and Sigmoid are two common activation events. Image elements are automatically extracted using segmentation and a continual accumulation of convolutional processes, integration functions, indirect opening functions, and other completely integrated layers. Then, by evaluating these derived characteristics, it is possible to extract pneumonia from the photos processed by the model. The model's general capacity is increased by fully utilising pixel-level image information. The most prominent neural framework has been proposed in past few decades for in-depth learning development, such as AlexNet [8] and VGGNet [9]. However, when the number of layers in the network increase, Instead of learning the numerous productive features, the neural network will be modified to particular parts of the training image, which makes the model similar to the capacity declines and creates congestion. The remaining communication framework was proposed to overcome the problem of network depth. Since then, neural networks have advanced, garnered a lot of attention and research, and have formed the foundation for a lot of occupations. We also looked at the efficiency of residual connections in our reduced CNN architecture with only a few layers in this study. S. L. Bangare et al. [10-17] have worked in the brain tumor detection. N. Shelke et al [18] given LRA-DNN method. Suneet Gupta et al [19] worked for end user system. Gururaj Awate et al. [20] worked on Alzheimers Disease. P. S. Bangare et al [21] worked on the object detection.

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

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Impact Factor: 6.252

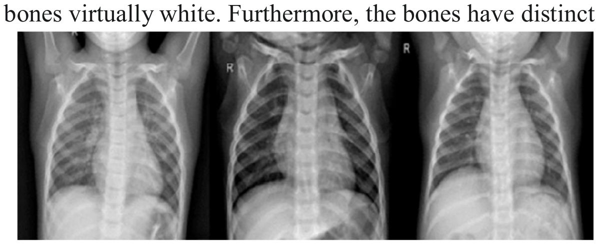
Kalpana Thakare et al [22-27] have worked on various machine learning algorithms. M. L. Bangare et al. [28] worked on the cloud platform.

IV. Materials and Methods

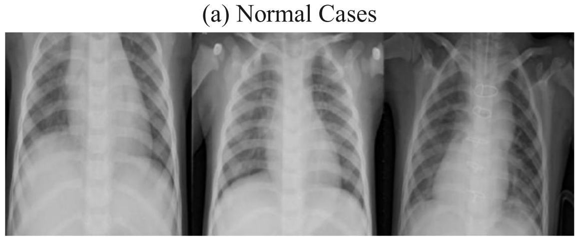
4.1 Data

The proposed database, which will be used to test the model's performance, comprises a total of 5863 X-ray pictures via Kaggle. Dr. Paul Mooney created a Kaggle contest in 2017 to classify viral and bacterial pneumonia. It differs from the other datasets since it contains 5,863 paediatric photos. We're talking about the updated version of this dataset.**[6]**

The database is further divided into three folders (train, test, and val) with subfolders for each image category (Pneumonia / General). Figure 1 shows a few instances of common and pneumonia photos that have been scaled to a static size. Due to the low amount of exposure in patients, chest X-ray images always show symptoms of limited brightness, and chest X-ray images always have black, white, and grey pants. The lungs are on both sides of the thoracic cavity, and the lung area is plainly visible on an X-ray since it is virtually black. The heart, which is situated between the lungs, appears practically as white as X-rays can go through it entirely. Because bones are comprised of protein and are exceedingly dense, X-rays cannot pass through them, leaving the bones virtually white. Furthermore, the bones have distinct edges.



(a) Normal Cases



(b) Pneumonia Cases

Figure 1: Examples from the dataset

4.2 Data Preprocessing

Table 1 lists the tactics employed throughout this article. Rescale is a value that we will multiply the data by before any other processing in our investigation. Our original photos had RGB coefficients ranging from 0 to 255, but values like this would be too high for our models to handle (given a typical learning rate), so we scale them down by a factor of 1./255. shear range is used to apply shearing transformations at random. When there are no assumptions of horizontal asymmetry, zoom range is used to randomly zoom inside photographs, and horizontal flip is used to randomly flip half of the images horizontally (e.g. real-world pictures). Data pre-processing techniques used in this study

Rescale	1./255
Zoom Range	0.2
Shear Range	0.2
Horizontal_Flip	True

Table 1

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

Volume 2, Issue 3, May 2022

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4.3 Proposed Network

In this study, we designed a VGG-based CNN model to extract the features of chest X-ray images and use those features to detect if a patient suffers from pneumonia. In Our CNN Architecture, We started with a lower filter setting of 32 and worked our way up layer by layer. A layer of Conv2D was used to build the model, followed by a layer of MaxPooling. An odd number, such as 3x3, is desirable for kernel size. The activation functions Tanh, ReLU, and others can be employed, but ReLU is the most popular. input shape accepts the width and height of an image, with the last dimension serving as a colour channel. After that, we flattened the input and added ANN layers.

$$S(x) = \frac{1}{1+e^{-x}}$$

f(x)=max(0,x)

S(x) = Sigmoid

f(x) = ReLU

For the last layers (ANN Layers), I used a softmax activation function and defined units as the total number of classes. For binary classification, I used a sigmoid and set the unit to 1.

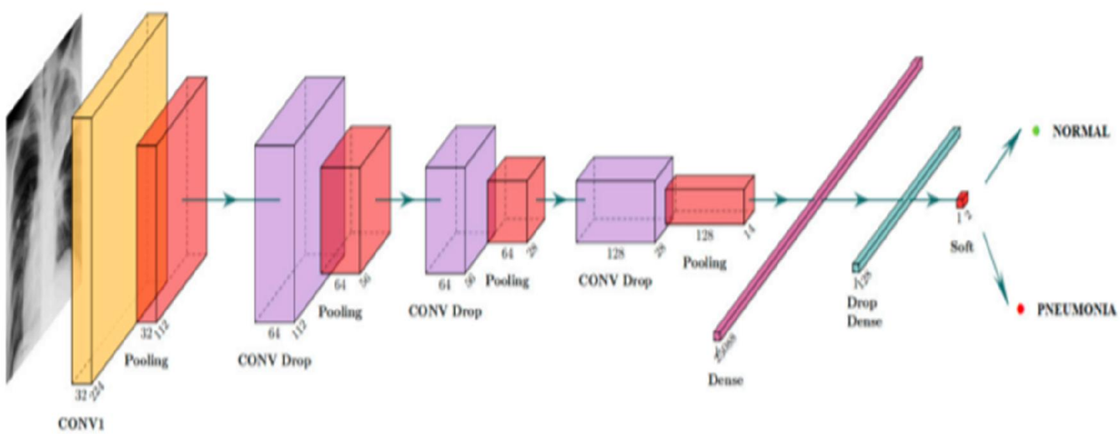

Figure 2: Details of proposed DL model.

V. Implementation

Convolutional neural networks are a type of neural network that shares all of the characteristics of other neural networks. CNN, on the other hand, was created specifically to process input images. The architecture of their organisation is therefore more specific: it is made up of two primary parts.

5.1 Conv Layers

Because it works as a feature extractor, the first block establishes the uniqueness of this sort of neural network. It accomplishes this by adding convolution filtering processes to template matching. The first layer uses many convolution kernels to filter the image and produce "feature maps," which are then normalised (using an activation function) and/or shrunk.

5.2 Pool Layers

The second block is not unique to CNNs; in fact, it appears at the end of all categorization neural networks. To return a new vector to the output, the input vector values are transformed (using various linear combinations and activation functions). The chance that the image corresponds to class I is represented by element I of this last vector, which has as many elements as there are classes. As a result, each element has a value between 0 and 1, and the total value is 1. The last layer of this block (and hence of the network) calculates these probabilities using a Sigmoid function (binary classification) or a RELU function (multi-class classification) as an activation function.

IJARSCT

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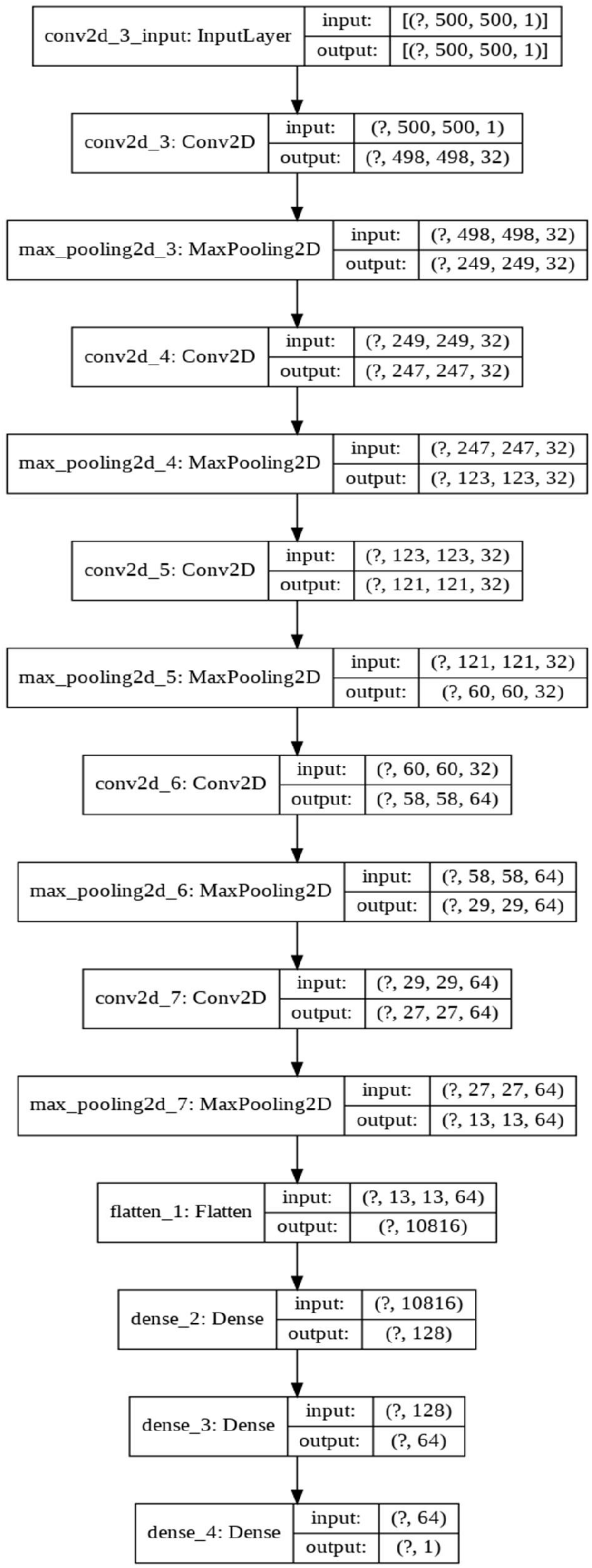


DOI: 10.48175/IJARSCT-3851

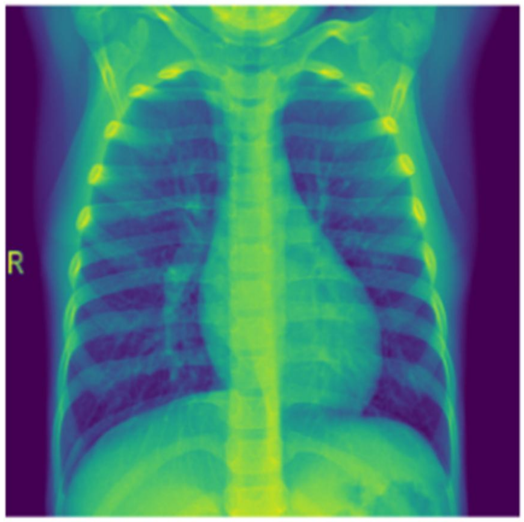
5.3 Fitting Model

EarlyStopping is a function that allows you to halt the epochs early based on a measure. It aids in the avoidance of overfitting the model. We're urging you to stop based on the val loss statistic since it needs to be as low as possible.

Patience states that once a minimum val loss is attained, if the val loss grows in any of the next three iterations, the training will end at that epoch. EarlyStopping in our training session came to a halt in the 9th epoch, with val loss = 39.8% and val accuracy = 68.7%. when the patience level is 3

Actual test results were 91.98 percent accurate on the model.

99.35% probability of being Normal case
Actual case : NORMAL



- This provides you a percentage estimate of the individual image, which you may load straight from your hard drive by specifying its path.
- After importing the image as we did previously, we must recreate all of the data pretreatment procedures in order to input the test set into the model and obtain a forecast. Importing the tensorflow. keras.preprocessing. image class is required for pre-processing.
- Import an image with dimensions of (500,500) and a grayscale colour channel.
- To predict the case, convert the image to an array, rescale it by dividing it by 255, and extend dimension by axis = 0 as shown earlier.

VI. Conclusion and Future Work

This paper presents an automated diagnosis of pneumonia in X-ray scans using deep CNN. The research was conducted utilising the X-Rayscan dataset, which contains 5863 scans. Experiments yielded a variety of scores, including accuracy, recall, precision, and AUCranking, proving the efficiency of our network model. The proposed framework was successful in reaching a 91 percent categorization accuracy. To improve the model's efficiency, hyper-parameter optimizations were examined, and multiple optimization techniques, such as stochastic gradient descent, Adagrad, and Adamoptimizer, were used. The customizedVGG16 model's effectiveness in detecting pneumonia reveals that the model surpasses other optimizers when compared to Adam.In the future, this research will be broadened to include the detection and differentiation of multi-class X-ray images. The efficiency could also be improved by applying more complex feature extraction approaches based on many recently established deep learning models for biomedical picture segmentation.

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