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An Automated Deep Learning System for Accurate Identification of Pneumonia and Covid-19 from Chest X-Ray Images

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Abstract: Deep learning (DL), which has been developing rapidly over the past few years and is now very helpful in an array of sectors thanks to the increasing data readily accessible, The primary purpose of DL technology is to make decisions in a more timely, dependable, and accurate manner. As a result of this capacity, DL has found applications in the medical field, especially with the intention of concentrating on different kinds of medical imagery or visuals that are relevant to the patient's health. The diagnostic procedures used in these areas are reliant on the gathering and analyzing of a substantial quantity of medical images. This research presents a DL algorithm for identifying Pneumonia and Covid-19 utilizing Chest X-Ray images. The model is built on something called a "Convolutional Neural Network (CNN)". The outcome of this analysis enables the radiologist to extract insights and make decisions that assist them decide the patient's accurate diagnosis. This model is useful in two different respects. In the initial place, it is necessary to determine if a chest x-ray displays any alterations in relation to COVID 19 and infection. The second stage is to categorise the results using images of a computed tomography x-ray. The VGG16 model performed better than Inception V3 (IV3) model using multiple performance metrics. A web application to help radiologists gain perspectives and make judgements to perform accurate medical prognosis was also developed.

Keywords: Deep learning, Convolutional Neural Networks, Inception V3, VGG16, chest X-Rays, Covid-19, pneumonia

1. INTRODUCTION

In December of 2019, scientists in Wuhan, China, discovered the "Novel Coronavirus. More than 200 countries had reported instances of covid19 by the end of March 2020, with an estimated 7 lakh infections and over 30,000+ deaths globally. Young people, institutions, and the public at large all face perilous danger from this deadly disease. Pneumonia affects children more often than any other respiratory lung condition. Little children (those younger than five years old) are particularly vulnerable to developing pneumonia. Over 7 lakh children worldwide are at danger of passing away each year from pneumonia. Almost 7% of the world's population is impacted. It has been hard to identify whether a person has Covid or pneumonia from chest x-rays, even by highly trained radiologists [1].

In order to foresee these diseases in persons, however, we need the aid of computerised technology. In light of this, it is proposed here to apply a model built on digital chest x-ray images for accurate diagnosis of Covid19 and pneumonia. Radiologists and physicians could benefit from this in drawing conclusions. We demonstrate a technique that makes use of multiple DL models, namely how the IV3 and VGG16 models may be used to correctly identify both conditions. In this form of supervised learning, CNN is used to make predictions about the results. To increase the size of the training set uniformly, the right data enrichment procedures are used. Lastly, the effectiveness of the model is evaluated to find out how well it predicted the images. As a result, radiologist routinely use the trained model for the fast detection of Covid19 and pneumonia.

Recently, "computer-aided designs" (CAD) have become an important topic in deep learning (DL) studies. The present CAD system has shown its worth in assisting doctors, especially in the areas of interpreting radiograph, mammograms, terminal illness, and so on. The crucial components are necessary for using DL methods to medical scans. So, traditional approaches to developing image-viewing software typically emphasized the usage of bespoke features. Unfortunately, the hand-made parts have limitations in terms of providing practical functionality because of their inherent volatility. DL models, in particular CNNs, have proven to be very helpful for extracting actionable attributes for computer vision [2].

It is feasible to share the knowledge and characteristics discovered by a pre-trained CNN model when working

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on a huge database, such as ImageNet. Such transfer learning techniques are necessary in the attribute mining procedure. The accessibility of pre-trained CNN models, such as VGG16 and IV3, plays a crucial role in achieving high-quality extraction of features. Moreover, the classifier with increased retrieved attributes improves classification efficiency [3].

As Covid19 has already spread to more than 150 nations, the “World Health Organization (WHO)” has classified it as a pandemic. Over 19 lakh confirmed cases of COVID19 were reported by the end of the second week in April 2020, with over 1 lakh deaths. Similarly, pneumonia has surpassed all other causes of death among children as the largest infectious killer in the modern age. According to a World Health Organization study, pneumonia kills millions of children younger than seven years old every year [4]. T Because of this, it is now considered as a top killer worldwide. In our work, we have used a reliable and efficient technique for identifying COVID-19 and pneumonia. The DL model employed digital chest x-rays to differentiate among healthy, Covid19-positive people and those with pneumonia. The decision-making and diagnostic flexibility of this system will be of considerable use to physicians as well as other medical practitioners.

A strategy for detecting pneumonia and Covid-19 by applying DL was the primary focus of this work. In this research, we employed DL techniques, specifically the IV3 and VGG16 models. In addition, a web app was produced that can analyse uploaded radiograph images to determine if a person has a healthy immune system or is sick with Covid/Pneumonia.

Predicting the onset of Covid19 and pneumonia disease using DL models including IV3 and VGG16 was the primary objective. The following steps were taken to accomplish this objective:

- Single chest x-ray images were obtained from [5] and subjected to pre-processing and data categorization. Specifically, we had to do some preliminary analysis on the information, which entailed setting the images up to be enhanced and balanced with additional data. Throughout data pre-processing, these unique X-ray pictures were split up into train, test, and validation databases. They were improved and regulated.
- At the model-building phase, we used the IV3 and VGG16 algorithms to sort images into 3 groups: normal, covid19, and pneumonia. CNN used a suite of optimization methods to mine the imagery for a wide range of data. The majority of the chest x-rays are monochrome. In order to accomplish this, we used trained versions of the IV3 and VGG16 algorithms.
- The accuracy and loss were utilized to evaluate the trained IV3 and VGG16 algorithms on the test images of chest x-rays, and the algorithms were then deployed in a web service. We utilised the ”Django” python technology to turn the model into a working web service.

Following are the key research contributions and novelty of this work:

- Designed a DL model for identifying pneumonia and Covid-19 on chest X-ray images retrieved from the database [5].
- On a test dataset, we compared the effectiveness of various DL techniques in terms of accuracy and loss.
- Normal, covid, and pneumonia-affected images were classified using a multi-class approach.
- Multiple performance metrics such as accuracy, precision, recall, sensitivity, and loss were utilized to evaluate the models.
- Created a web software to help radiologists gain perspectives and make judgements to perform accurate medical prognosis.
- The designed DL model is useful in two respects. First, to categorise if a chest x-ray reveals any abnormalities in relation to Covid 19 and pneumonia. Second, to categorize utilizing typical chest x-ray images as reference.
- Our research adds to the growing amount of literature on the application of DL technique to healthcare, and more especially to the identification and assessment of Covid-19 and pneumonia.

2. Related work

This section discusses the relevant work performed in the detection of Covid-19 and Pneumonia using DL models.

The research work [6] discusses the impact of COVID-19 on human life and economies. The study shows that older adults and people with a history of pneumonia are at a greater risk of acquiring serious COVID-19 consequences.. To detect the infested areas of the lungs, chest X-ray is commonly utilized, and the research employs ML tools to build a detection model for pneumonia in COVID-19 patients. The system was constructed using a number of DL models, including CNN, VGG16, AveragePooling2D, dropout, flatten, dense, and input.

The research work [7] aims to develop a CAD prototype for detecting pneumonia in X-ray images quickly and accurately, which is essential for early treatment and prevention. With the outbreak of COVID-19, chest radiography has become a major resource for identifying COVID-19-infested pneumonia. The study [7] employs DL techniques such as “transfer learning” and “parallel computing” to build a DL-based CAD system using well-known DL models like VGG19 and ResNet50. The authors tested their model on the "COVID-QU-Ex" repository of X-Ray imageries having 3 classes, Pneumonia that was infested with COVID-19, illnesses that were not caused by COVID-19, and healthy images.

The purpose of the study [8] is to use X-ray imaging, that are one form of healthcare imagery used to assess respiratory disease, to classify individuals with COVID-19 and pneumonia. In this research, pulmonary X-ray imagery from the actual world are used with an appropriate convolutional neural network (CNN) model to detect COVID-19 and pneumonia individuals. The images are healthy, COVID-19, and pneumonia trained, among other categories. All forms of pneumonia, including both viral and bacterial pneumonia, are detectable with their approach, not just COVID-19. For the purpose of automating the categorization and detection of COVID-19 pneumonia from chest X-ray imaging, the researchers of [9] created a DL method that performs particularly well. They presented a three-step procedure for imaging detection and classification, including visual improvement, up-sampling, and TL methods. The research was done using a public database of chest X-rays.

Employing CT and X-ray scans, the investigators of the research [10] created an AI tool to categorise the person's pulmonary inflammatory degree (moderate, progressing, serious phase). Stage one of their system used Morphology techniques to determine the thickness and volume of CT scan tumors as well as aperture settings. In the second phase, a modified CNN and k-Nearest Neighbor were used to categorise the severity of pneumonia in the validated COVID-19 case. The pre-trained customized CNN approach was then trained on a repository using the TL approach.

The significance of prompt COVID-19 identification and diagnosis in limiting the transmission of the virus was addressed by the scientists in [11]. Alternate rapid diagnostic procedures are desperately required because conventional analysis techniques are cumbersome and limited in availability. In their research, the authors looked at DL algorithms as a possible means of early diagnosis of COVID-19. Scientists go over the literature's several methods for detecting COVID-19, laying out their pros and cons and looking ahead to the difficulties that lie ahead for DL-based methods. They recommend utilising CT and X-ray visuals of the chest, as these offer a better complete view of the patient's lungs and allow DL methods to effectively identify cases of viral pneumonia. The authors also highlight recent developments in coughing detection and human movement prediction as potential tools for limiting the spread of COVID-19.

The paper [12] examined the diagnostic applications of DL in the medical field of scanning. To identify COVID-19 and pneumonia in X-ray visuals in genuine, a desktop DL model named COVID-CXDNetV2 was created. The algorithm was developed on a big database of X-ray imagery labelled as COVID-19, pneumonia, and healthy, and it is built on YOLOv2 plus ResNet.

Chest X-rays and CT scans can be used for early identification of pneumonia and COVID-19, as discussed by the scientists [13]. Present diagnostic procedures for these disorders necessitate the appearance of skilled physicians and a significant duration. DL techniques , therefore, could make the method for recognizing pneumonia and COVID-19 more rapid and comprehensive. Community-acquired pneumonia, viral pneumonia, and COVID-19 may all be detected from chest X-rays and CT scans, and the article [13] reviews the latest developments in DL algorithms for doing so. Several DL model designs were described, along with the problems they solve and the costs and benefits of adapting a design to satisfy particular criteria. The report detailed a quantitative analysis of the simulations to compare the efficiency of various approaches to the same problem. The purpose of their study was to be a one-stop-shop for newcomers and established academics alike by collecting and analysing a significant quantity of study materials, including data sources, model designs, and outcomes, in a central site.

Employing U-Net and ResNet-50, the authors of [14] set out to create a DL technique to aid physicians in the detection of COVID-19 pneumonia. Using a sample size of 437 and a training phase of 26,477 CT scans, the researchers evaluated the model's detection precision in relation to that of various levels of physicians. In their work, the researchers discovered that a DL algorithm might help physicians identify COVID-19 pneumonia.

The work [15] aimed to develop a system using DL methodologies to detect Covid-19 patterns in "radiation-free lung ultrasound (LUS)" tomography. The researchers used a reliable dataset comprising ultrasound clips from 400+ hospitalized patients and performed an analysis into identifying Covid-19 samples and placing them according to difficulty measures. The authors used residual CNNs, TL, and information augmentation methods to produce effective outcomes. The researchers concluded that their approach using DL and LUS imaging could be a reliable diagnostic tool for Covid-19 pneumonia, especially in settings where CT scans are not available or practical.

The study [16] proposes an improved segmentation model called ResAU-Net for detecting and segmenting coronavirus pneumonia using CT scans. The ResAU-Net includes attention, residual, and sub-pixel convolution modules. Lung segmentation is performed using U-net, and the "region of interest" is chosen using the least delineated frame cropping technique. The model was evaluated on 99+ upper body CT imageries using cross-validation, achieving improved performance on the pneumonia records.

Following points highlight the limitations of existing works over proposed work and how they are overcome in the proposed work.

- The work [6] focuses only on the detection of

COVID-19-induced pneumonia, while the proposed work also includes the detection of COVID-19 and pneumonia separately. This is an important distinction as it enables healthcare professionals to accurately diagnose and treat patients based on their specific condition. Secondly, the proposed work uses a more advanced deep learning algorithm, InceptionV3, in addition to the VGG16 algorithm used in [6]. This allows for a more comprehensive evaluation of the effectiveness of different DL techniques in identifying COVID-19 and pneumonia. Thirdly, the proposed work includes the creation of a web software to assist radiologists in making accurate medical prognosis, while [6] does not mention any such tool.

- The work [7] used only one dataset COVID-QU-Ex, while the proposed work uses a dataset containing images of persons with COVID-19 and pneumonia, along with the images of regular chest x-rays. The use of only one dataset may limit the generalizability of the results. The proposed work focuses on detecting COVID-19 and pneumonia, while [7] only focuses on detecting pneumonia. As a result, the proposed work covers a broader range of medical conditions and is more comprehensive. The proposed work uses multiple performance metrics such as sensitivity, specificity, precision, recall, accuracy, and loss to evaluate the DL models, while [7] only reports average classification accuracy. A more comprehensive evaluation of performance metrics would be better in determining the effectiveness of the DL model. The proposed work includes the creation of a web software to help radiologists gain insights and make accurate medical prognoses. In contrast, [7] does not include any information about software development for assisting radiologists. The proposed work suggests that adjusting the hyperparameters could increase the accuracy of the model in later studies. [7] does not discuss the adjustment of hyperparameters or any potential areas of improvement for the DL model. The proposed work employs a multiclass strategy to categorize normal, COVID, and pneumonia-affected images, while [7] uses a binary classification approach. Our work's multiclass approach may be more useful in detecting and diagnosing pneumonia and COVID-19 in real-world scenarios.

- The proposed work uses a dataset containing imagery of persons with COVID-19 and pneumonia along with images of regular chest X-rays. In contrast, [8] uses a specific dataset (COVID-QU-Ex) that may not represent the population's variability and diversity. This could limit the generalizability of the devised model to other datasets. Our work uses multiple performance metrics to evaluate the DL models. In comparison, [8] only reports the average classification accuracy, which could provide limited information about the model's performance. The proposed work creates a web software to help radiologists gain perspectives and make judgments to perform accurate medical prognosis. [8] does not mention the creation of any such software, which could limit its practical application. Accuracy of [8] was 96.6% and accuracy of proposed work was 98.03.

- The study [9] only focuses on COVID-19 pneumonia, while the proposed work also includes the detection of pneumonia not triggered by COVID-19. This limits the scope and applicability of the study [9]. The proposed work uses a more diverse dataset that includes normal, COVID-19, and pneumonia-affected images, while [9] only includes images of chest X-rays classified as Normal, COVID-19, Lung Opacity, and Viral Pneumonia. This could limit the ability of the [9] model to generalize to a wider range of cases. The proposed work uses a multiclass approach for classification, while the study [9] only uses binary classification (COVID-19 or non-COVID-19). The multiclass approach used in the proposed work is more comprehensive and could provide more useful information to healthcare professionals. The proposed work includes the creation of a web software to assist radiologists in making accurate medical prognosis, while [9] study does not mention any practical applications or tools to assist medical professionals. The proposed work achieves a higher accuracy rate of 98.03% compared to the 95.63% achieved in the study [9]. While both studies achieve high accuracy rates, the proposed work outperforms the study [9] in terms of accuracy.

- The study [10] focuses only on classifying the pneumonia level of COVID-19 patients using CT scan images, whereas the proposed work focuses on detecting COVID-19 and pneumonia using chest X-ray images. The study in [10] only evaluates the testing accuracy of the developed models. In contrast, the proposed work uses multiple performance metrics such as sensitivity, specificity, precision, recall, accuracy, and loss to evaluate the DL models' effectiveness. The study [10] only compares the developed model's performance with other classification algorithms, while the proposed work compares the performance of different DL techniques, including state-of-the-art models such as InceptionV3 and VGG16. The modified CNN model in 10-Springer is trained on a relatively smaller dataset than the original dataset, which may affect the model's performance on unseen data. In contrast, the proposed work uses a larger dataset obtained from a repository. The proposed work not only detects COVID-19 and pneumonia but also provides a web software to assist radiologists in making accurate medical prognoses. In contrast, the study [10] is limited to the classification of the pneumonia level of COVID-19 patients. Web software was also not developed in [10].

- The work [11] is a review and does not develop any DL-based method as the proposed work. Furthermore, it focuses only on Covid detection while the proposed work focuses on both Covid and pneumonia detection.

- The dataset used in our effort contained more than 3700 examples of 3 classes named COVID-19, pneumonia, and normal, whereas the dataset used in [12] is not mentioned, making it unclear how representative the dataset is. he proposed work used the VGG16 model for COVID-19 and pneumonia detection, while [12] used the COVID-CXDNetV2 model based on YOLOv2 with ResNet. There is no comparison of these algorithms, making it difficult to determine which algorithm is more effective. The proposed work created a web software to assist radiologists in making accurate medical prognosis, while [12] did not mention any such tool.

- The paper [13] is a systematic review and does not present a new DL model for identifying Covid-19 and pneumonia, whereas the Proposed work presents a new DL algorithm for this purpose. The paper [13] does not present a web software to help radiologists gain insights and make accurate medical prognosis, whereas the Proposed work includes the creation of such software.

- The scope of [14] is limited to COVID-19 pneumonia, while the proposed work includes the identification of both COVID-19 and pneumonia on chest X-ray images. The proposed work developed a web software to help radiologists gain perspectives and make judgments to perform accurate medical prognosis, while the [14] did not include such a tool. The study [14] only compared the diagnostic accuracy of the DL model with various stages of radiotherapists, while the proposed work utilized multiple performance metrics to evaluate the DL models' accuracy, sensitivity, specificity, precision, recall, and loss. The proposed work also suggests future improvements to the model, such as adjusting the hyper-parameters and exploring alternative CNN architectures, while [14] does not provide any suggestions for future research. The sample size of the study [14] is relatively small, with a total study population of 437, while the proposed work used a larger dataset of 6432 containing imagery of persons with COVID-19 and pneumonia as well as images of regular chest x-rays.

- The study [15] only focuses on the use of LUS imaging for detecting Covid-19 patterns, whereas the proposed work also considers the use of chest X-ray images to identify Covid-19 and pneumonia. The work [15] only evaluates the performance of the DL model using the F1 score, whereas the proposed work uses multiple performance measures to evaluate the DL models. The research [15] has a limited dataset comprising ultrasound clips from 450 hospitalized patients, whereas the proposed work uses a larger dataset of 6432 chest X-ray images. The work [15] only concentrates on the severity scales of Covid-19 patterns, whereas the proposed work uses a multiclass approach to classify normal, covid, and pneumonia-affected images. The work [15] does not provide any information about the creation of a web software to help radiologists gain perspectives and make judgments to perform accurate medical prognosis, which is one of the key contributions of the proposed work. The authors in [15] do not discuss the adjustment of hyperparameters to enhance the model's accuracy in later studies or the possibility of using alternative CNN architectures, which the proposed work addresses.

- The paper [16] focuses solely on the dissection of COVID-19 lacerations using CT scan images, while the proposed work uses DL algorithms to detect and categorize COVID-19 and pneumonia using chest X-ray images. As a result, the proposed work has a broader scope and can provide more insights into the diagnosis and treatment of these diseases. The paper [16] did not evaluate the performance of their ResAU-Net model with additional techniques. In contrast, our work compares the effectiveness of various DL techniques and algorithms, including InceptionV3 and VGG16, in detecting COVID-19 and pneumonia. This comparison provides more evidence for the validity and reliability of the proposed DL model. The paper [16] only evaluates the performance of their proposed ResAU-Net model using mIoU and Dice coefficients for lesion segmentation. In contrast, the proposed work uses multiple performance measures to assess the effectiveness of their DL models. This broader range of evaluation metrics provides a more comprehensive assessment of the DL models' performance. The paper [16] only evaluates their proposed ResAU-Net model using 100 chest CT scans test images, which may not be representative of the entire population. In contrast, the proposed work uses a dataset containing 6432 imagery of persons with COVID-19 and pneumonia with the images of regular chest X-rays. This larger and more diverse dataset provides a more robust evaluation of the DL models' performance. While the 16-Annals paper proposes a novel method for segmenting COVID-19 lesions, it does not provide practical applications or tools for medical practitioners to use in their diagnosis and treatment of patients. In contrast, the proposed work created a web-based software to help radiologists gain perspectives and make accurate medical prognosis, which can be a valuable tool for medical practitioners in their clinical practice.

3. Dataset

Table I shows the dataset details obtained from the repository [5], which comprises images of normal, covid, and pneumonia patients. The dataset contained 6432 images in whole.

TABLE I. Dataset details

Images	Classes	Number of Images
Training data	Covid-19	460
	Normal	1266
	Pneumonia	3418
Test Data	Covid-19	116
	Normal	317
	Pneumonia	855

Table I shows that there were 5144 images in the training examples and 1288 in the testing data. Records are broken down per category in Figure 1. There were more examples of pneumonia in both the training and test data sets.

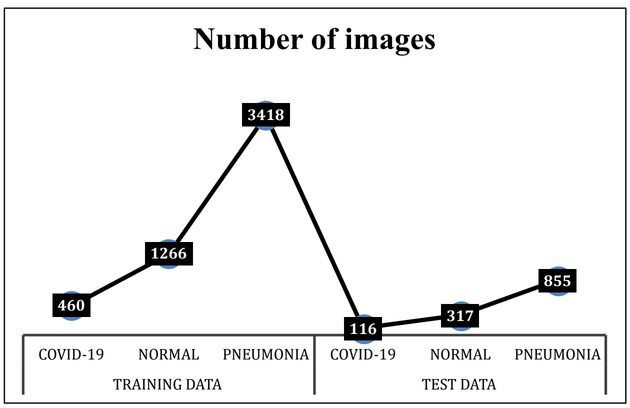

Figure 1. Class wise distribution of records

The training dataset was employed to train the IV3 and VGG16 models, which were then tested on the evaluation dataset. A multiclass analysis was undertaken, with the results separated into the "normal," "covid," and "pneumonia" categories. Figure 2 displays a selection of the dataset's X-ray images, some of which are normal, some of which are of pneumonia, and some of which are of Covid-19.

Figure 2. Sample images in the dataset

4. Framework and System Design

In this segment, we examine the designed framework for the identification of Covid-19 and pneumonia. Figure 3 depicts the network topology used to identify pneumonia and Covid-19 using a IV3 and VGG16.

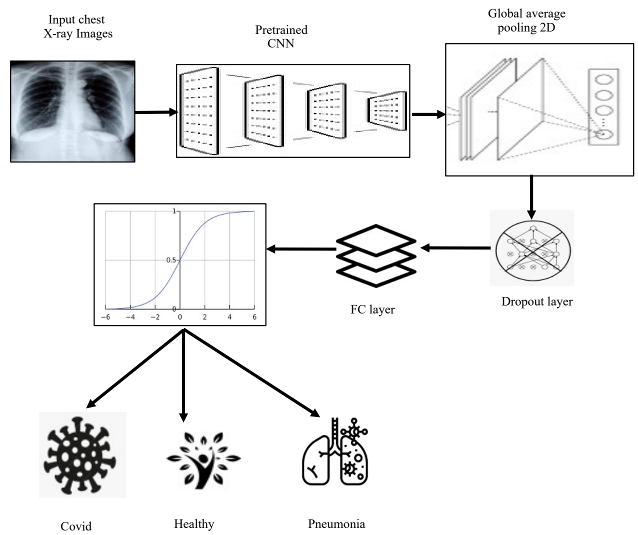

Figure 3. CNN architecture for Covid and pneumonia detection

As shown in Figure 3 images from three different categories—covid, pneumonia, and a normal chest X-ray—are being fed into a pre-trained CNN model. The images are converted to a 2D array by pooling in the CNN model. The dropout layer receives this information and uses it to prevent over-fitting. The information is then passed on to the final prediction layers, the fully linked layer and the SoftMax layer. Class architecture of the CNN model employed in this work is shown in Figure 4.

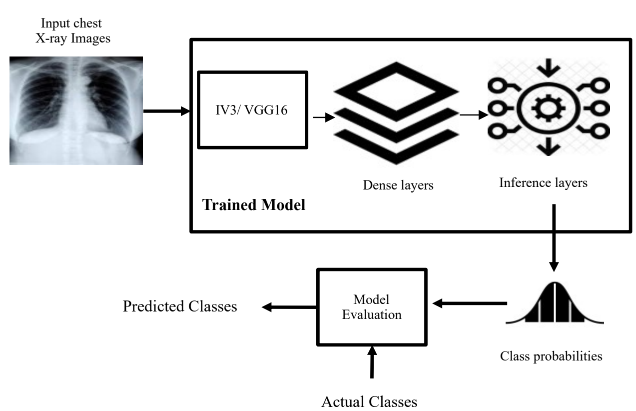

Figure 4. Class hierarchy of CNN model

Chest X-rays can fall into one of three categories: category 0 is for normal images, category 1 is for covid images, and category 2 is for pneumonia images. In order to forecast and classify these 3 kinds, CNN techniques are used (IV3 and VGG16). For this purpose, we compared the DL models' projected classifications to the actual classifications in order to calculate performance indicators. The work's sequence model for detecting Covid and pneumonia is depicted in Figure 5.

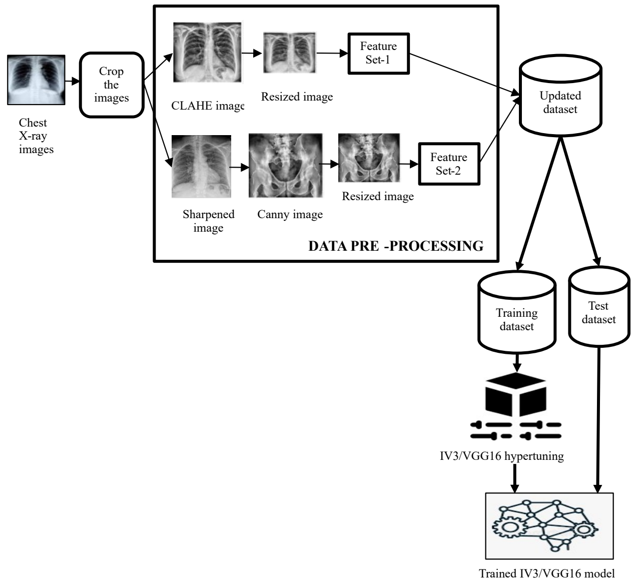

Figure 5. A sequence model for identifying cases of Covid-19 and Pneumonia

Before the actual processing can begin, the chest X-ray images must be reduced to the proper dimensions and given the appropriate preprocessing. To improve the legibility of the chest x-ray pictures, "Contrast limited adaptive histogram equalisation" (CLAHE) was used during the preprocessing phase. This final image was called the Feature Set-1. The initial blurry images were refined into a clearer, more defined image. As a result, we have Feature Set-2. The new dataset is a mixture of attribute sets 1 and 2. The classification technique was carried out after the images had been preprocessed. At this point, the refreshed data set was partitioned into a set of test cases and a set of illustrations. To construct the trained IV3/VGG16 model, hyper-tuning of the IV3 and VGG16 algorithms was carried out on the training examples. The test set data was employed to assess the trained IV3/VGG16 model. Compared to the IV3 model, the findings revealed that the VGG16 model was more effective at segmenting the chest x-ray images into normal, covid-19, and pneumonia categories.

A. Inception V3 model

The inception V3 framework used in this research is shown in Figure 6.

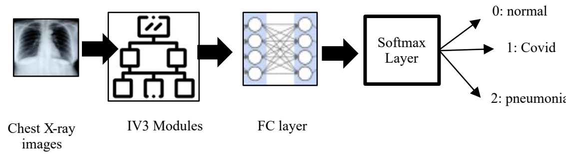

Figure 6. Inception V3 model for Covid-19 and pneumonia detection

The IV3 model is used for image classification; it is a CNN-based DL prototype. It's an upgraded version of Google's original Inception V1 from 2014. The Googlenet platform is responsible for these virtual environments. It is built with convolutional and pooling layers. Convolution is a method that applies a kernel to each pixel in an image sequence, modifying the pixels immediately surrounding that pixel as the sequence progresses. Pooling is used to lower the size of the feature mapping. Most people use either a maximal or an average pooling strategy.

Figure 6 shows the IV3 model being fed data consisting of normal, covid-19, and pneumonia images. The Inception-v3 model is a 48-layer CNN. The infrastructure of an Inception v3 network is built up in stages as described below:

- The computation efficiency may be improved by reducing the amount of connectivity parameters by using factorised convolutions. Furthermore, it keeps an eye on the system's efficiency.
- By using smaller convolutions rather than bigger ones, training duration could be decreased. For comparison, the identical combination utilising twin 3-by-3 filtration only has 18 parameters (3*3 + 3*3), whereas a 5x5 filter has 25.
- Owing to asymmetrical misrepresentations, a 3x3 combination could be transformed into a 1x3 convolution, which is then followed by a 3x1 convolution. By replacing a 3x3 convolution with a 2x2 convolution, for instance, the proposed asymmetrical conjunction reduces the number of parameters required.
- A compact convolutional neural network (CNN) deployed among training levels, wherein loss is caused by the loss of the main network. In GoogleNet, auxiliary functions were used to build out the network, while in Inception v3, they play the role of a regularisation parameter.
- The length of a grid can be reduced through pooling operations.

All these concepts are condensed into a single diagram in Figure 8's IV3 sections. The outcome of IV3 is passed on to the fully connected layer which is the culmination of a feed-forward neural network. When a net is finished, the remaining strands are tied very securely. A flattened version of the output generated by the previous Pooling Layer is fed into the fully connected Layer. The output of the completely linked layer is passed to the SoftMax layer. The network output of the IV3 model are recommended to use the SoftMax activation function, indicating a multi-nomial probabilistic model. As multi-class classification (three classes: normal, pneumonia, and Covid-19) had to be conducted, SoftMax was employed as the final layer in this research. Inception V3's benefits include its high efficiency, its deeper network than Inception V1 and V2, and its robust 42-layer architecture.

B. VGG16 model

The VGG16 model, which can identify both Covid and pneumonia, is shown in Figure 7.

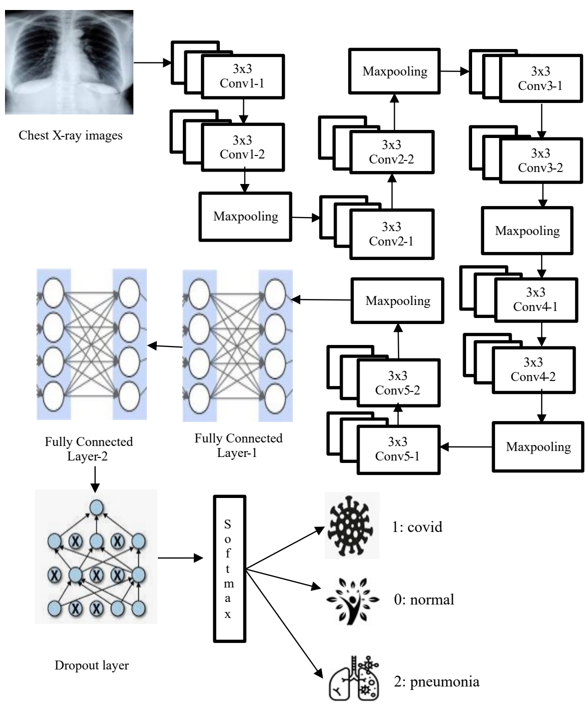

Figure 7. VGG16 model for Covid and pneumonia detection

The VGG16 is a 16-layer convolutional neural network model. Image classification is possible since it is a pre-trained technique. The simulation is fed an input with a predetermined RGB visual dimension of 224 X 224. To begin, the image is processed in via a series of completely interconnected layers, where the most fundamental concept of the respective disciplines is stored. After that step, pooling is finished with a maximum of 5 layers. Next, three completely linked levels are put to use, the first two of which feature 1000 units apiece and the latter 2, 4096 units apiece. SoftMax is the final layer and it calculates the likelihood of each target class. Each hidden component comprises a RELU, which helps limit the requirement of exponential growth in order to function as a NN. We examined Inception V3 and VGG16 in terms of accuracy and validation loss to establish which method is superior at identifying Covid19 and pneumonia disorders.

5. Results

Here, we show how the system functions in practise. The outcomes of all significant tests are summarised in an easy-to-understand format. CNN-based DL models like Inception V3 and VGG16 can be utilised for both image classification and prediction. We have evaluated various methods and analyzed their results. Modeling code was originally written in Jupyter Notebook before being moved to Google Collaboratory. The Django API links the CNN model in the back-end to the user interface in the front-end. Our web application, is built on top of the open-source Python web framework Django. Django was chosen because it is easier to learn, faster to implement, and produces a more polished final product. The relative accuracy and loss of the DL models for detecting Covid and pneumonia are shown in Figure 8.

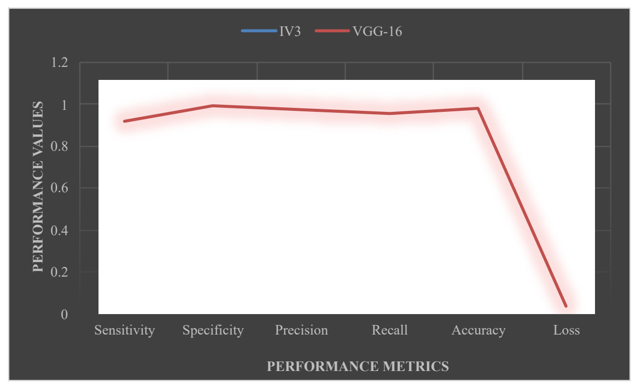

Figure 8. A comparison of the diagnostic capabilities of the IV3 and VGG16 models with regard to Normal, Covid-19 and pneumonia classification

Table II shows the performance values with respect to each performance metric for IV3 and VGG16 models for Normal, Covid-19 and Pneumonia classification.

TABLE II. Performance values of IV3 and VGG16 models

Performance metrics	IV3	VGG16
Sensitivity	0.8823	0.9211
Specificity	0.9411	0.9903
Precision	0.8823	0.9723
Recall	0.8823	0.9564
Accuracy	0.9215	0.9803
Loss	0.7402	0.0356

As can be observed from table II and Figure 8, the VGG16 model performed with an accuracy improvement of 5.88%, sensitivity improvement of 3.88%, specificity improvement of 4.92%, precision improvement of 9%, and recall improvement of 7.41% over the Inception V3 model.

Similarly, the VGG16 model achieved lesser loss of 0.7046 over the Inception V3 model on the test dataset. Fig 9 shows the accuracy and loss plots of the VGG16 model on training and validation datasets at different epochs.

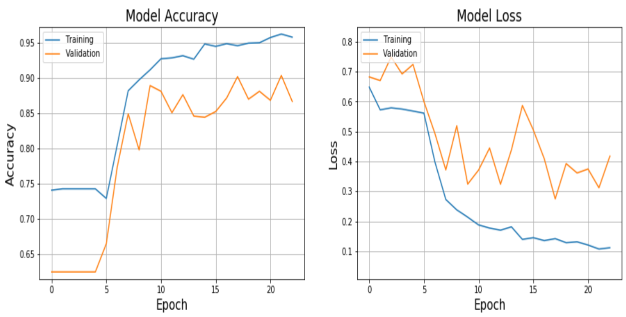

Figure 9. Plots of VGG16 model's accuracy and loss

It is evident that epochs 16 and 25 yielded the best validation accuracy and the least model validation loss. The confusion matrix for the top-performing VGG16 model is shown in table III.

TABLE III. Confusion matrix of VGG16 model on the test set

	Predicted Classes		
Actual Classes	Covid-19	Normal	Pneumonia
Covid-19	111	0	5
Normal	1	287	29
Pneumonia	0	35	820

From table III, it can be inferred that the VGG16 model was able to classify 111 records, 287 records, and 820 records correctly as belonging to the Covid-19, Normal, and Pneumonia classes respectively. However, the VGG16 model misclassified 5 records belonging to Covid-19 as Pneumonia, 1 normal record as Covid-19, and 35 pneumonia records as Normal. The VGG16 model outperforms Inception V3 because it is more generalizable and suffers from less overfitting. Because the addition of several non-linear layers increases the network's depth, the VGG16 model is able to learn more complicated features at a cheaper cost than the one with a bigger size kernel. While using 3X3 kernels, finer visual details are preserved. The screenshots of the web-based application created in this research for Covid-19 and pneumonia diagnosis are shown in Figures 10, 11, 12, and 13.

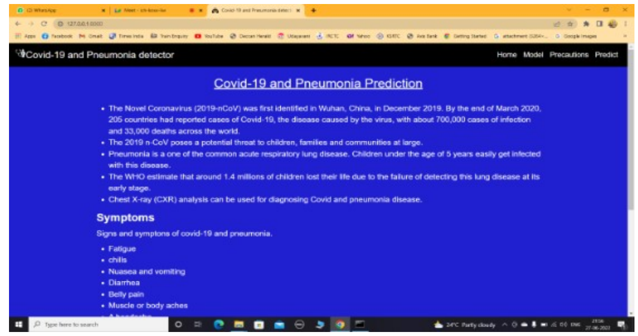

Figure 10. Webapp interface-1

Fig10 shows the user interface describing the details of the Covid-19 and Pneumonia illnesses.

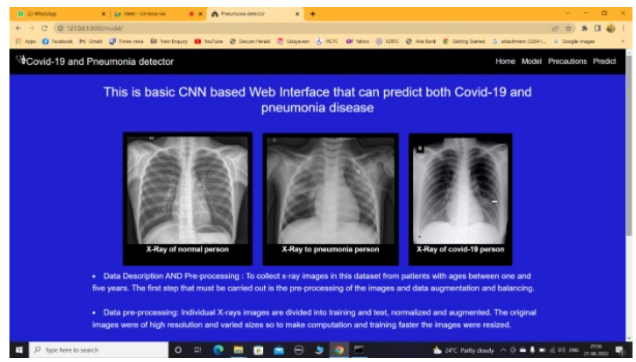

Figure 11. Webapp interface-2

Figure 11 depicts the user interface showing the chest x-rays of a normal person along with individuals affected with Covid-19 and pneumonia diseases.

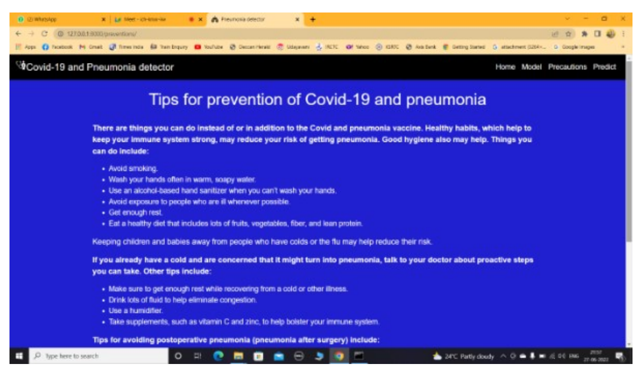

Figure 12. Webapp interface-3

Figure 12 shows the user interface describing the tips to be followed for preventing Covid-19 and pneumonia.

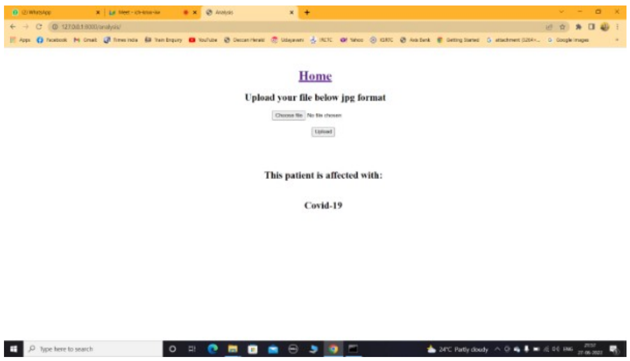

Figure 13. Interface for uploading Chest X-Ray images and prediction of Covid-19 and Pneumonia

The final user, typically a radiologist, will submit the chest x-ray image shown in Figure 13. When the chest X-Ray image is uploaded, our DL model that has been trained on chest x-rays will use it as a test image. The test can determine if an individual has good health or has Covid-19/pneumonia. As a back-end DL model, the best-performing VGG16 model was employed to make predictions.

6. Conclusion and Future Scope

This research uses CNN architectures and DL techniques to use computer vision to identify covid and pneumonia illness. The architecture for fine-tuning and extraction of features is often used as each discovered Convolutional Neural Network model is evaluated experimentally. From the repository, we have obtained a dataset containing imagery of persons with covid and pneumonia and the images of regular chest x-rays. Our analysis enabled us to identify the most potent algorithm for both covid and pneumonia detection among the two. We found that the VGG16 model outperformed the IV3 models that corroborate the authors' findings, with an accuracy improvement of 5%. Web application was also developed for assisting the doctors in gaining insights on Covid-19 and Pneumonia based on Chest X-Ray images. A novel method of identifying and diagnosing covid and pneumonia that could be useful in giving hospital services is suggested as a result of this work. The adjustment of the hyper-parameters ought to be one of the factors considered to increase the model's accuracy in later studies where the adaption of alternative CNN architectures, such as shuffling Net and Mobile Net designs, for the detection might be adopted. This research may also assist healthcare practitioners, such as doctors and other healthcare professionals, in making decisions about the use of more sophisticated prediction in genuine pneumonia detection as well as the possibility for detecting covid and pneumonia using deep learning methods.

Future scope for this research work includes the development of more robust models that can handle a larger dataset with varying degrees of disease severity. This will improve the accuracy and consistency of the DL methods. Furthermore, the integration of DL models with other diagnostic tools will enhance the accuracy of medical diagnoses. Additionally, the study can be extended to include the analysis of other medical images such as CT scans, MRI scans, and ultrasounds. Overall, the research work provides a promising foundation for the future development of DL-based medical imaging tools that will aid radiotherapists and medical personnel in doing timely and correct medical diagnoses.

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