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To Develop A Novel Method For Covid-19 Pneumonia In Lungs With Generation Of Appointment

Bhagyashri Gajanan Tekade
PG Scholar
Department of Computer Science
And Engineering
Government College of Engineering Amravati

Dr. P. B. Ambhore
Associate Professor
Department of Computer Science
And Engineering
Government College of Engineering Amravati

Abstract:

Recent studies show the potential of artificial intelligence (AI) as a screening tool to detect COVID-19 pneumonia based on chest x-ray (CXR) images. However, issues on the datasets and study designs from medical and technical perspectives, as well as questions on the vulnerability and robustness of AI algorithms have emerged. In this study, we address these issues with a more realistic development of AI-driven COVID-19 pneumonia detection models by generating our own data through a retrospective clinical study to augment the dataset aggregated from external sources. We optimized five deep learning architectures, implemented development strategies by manipulating data distribution to quantitatively compare study designs, and introduced several detection scenarios to evaluate the robustness and diagnostic performance of the models. At the current level of data availability, the performance of the detection model depends on the hyperparameter tuning and has less dependency on the quantity of data. InceptionV3 attained the highest performance in distinguishing pneumonia from normal CXR in two-class detection scenario with sensitivity (Sn), specificity (Sp), and positive predictive value (PPV) of 96%. The models attained higher general performance of 91-96% Sn, 94-98% Sp, and 90-96% PPV in three-class compared to four-class detection scenario. InceptionV3 has the highest general performance with accuracy, F1-score, and g-mean of 96% in the three-class detection scenario. For COVID-19 pneumonia detection, InceptionV3 attained the highest performance with 86% Sn, 99% Sp, and 91% PPV with an AUC of 0.99 in distinguishing pneumonia from normal CXR. Its capability of differentiating COVID-19 pneumonia from normal and non-COVID-19 pneumonia attained 0.98 AUC and a micro-average of 0.99 for other classes.

Introduction:

A supplementary to reverse transcription polymerase chain reaction (RT-PCR) in screening COVID-19 is imperative to augment the current global strategies in mitigating its continuous spread and potential future outbreak. Although RT-PCR testing is precise and considered as the gold standard for COVID-19 diagnosis, it is not easily accessible and scalable because of the costs and operational requirements [1–3]. Due to this limitation, radiologic-based approaches have been widely adopted for the initial screening of suspected cases. Preliminary studies showed that analysis of chest x-ray (CXR) images might lead to better sensitivity and specificity than RT-PCR-based diagnosis. Furthermore, the misdiagnosis rate of COVID-19 is very high and the misdiagnosis cost is expensive [4]. While the wide availability of CXR machines make it an attractive option for rapid and extensive screening, many radiologists had difficulty reading CXR due to the indistinct manifestation of radiological features such as consolidation and hazy increased opacities [5–8]. A technology-driven solution is to develop an artificial intelligence (AI)-based detection system that will facilitate an automated, accurate, and rapid COVID-19 pneumonia screening based on CXR images.

In recent years, medical diagnosis using AI-driven systems have demonstrated remarkable progress in assisting radiologists and clinicians for disease detection, characterization, and monitoring. The automated nature of AI to recognize intricate patterns in radiologic images and its ability to provide quantitative assessment offer an efficient and scalable mechanism to augment the current diagnostic workflow in the hospitals and ambulatory testing centers. There were preliminary works that utilized AI-driven methodologies to assist radiographic examinations in identifying the visual indicators highly associated with COVID-19. Wang et al. [2] introduced COVID-Net, a convolutional neural network (CNN) designed to detect COVID-19 cases using CXR images. The COVID-Net was trained using 13,800 CXR images to identify COVID-19-related cases and attained 92.6% accuracy and sensitivity of 97.0% (normal), 90.0% (non-COVID-19 pneumonia) and 87.1% (COVID-19). Recently, Basu et al. [9] trained AlexNet, VGGNet, and ResNet on a dataset consisting of 108, 379 CXR images derived from the US National Institute of Health to classify between diseased and normal CXR. These models were subsequently retrained via transfer learning using 1, 277 images and achieved 90.13% accuracy in distinguishing normal, other diseases, pneumonia, and COVID-19. A non-conventional approach in using transfer learning is to utilize the pretrained architectures as feature extractors. Turkoglu [10] extracted features using AlexNet, selected features using Relief, and classified the images using support vector machines (SVM) whereas Montalbo [11] concatenated the extracted features from two truncated Densenets and added a classification head. Another study trained AlexNet, GoogleNet, and ResNet and made the final prediction via majority voting [12]. In addition, several studies [13–16] have shown successful model development via transfer learning by incorporating data augmentation strategies such as rotation, translation, flipping and scaling to increase the number of training instances. Moreover, several works, albeit adopting different base architectures and development strategies, have also illustrated the potential of AI in detecting COVID-19 pneumonia using CXR images.

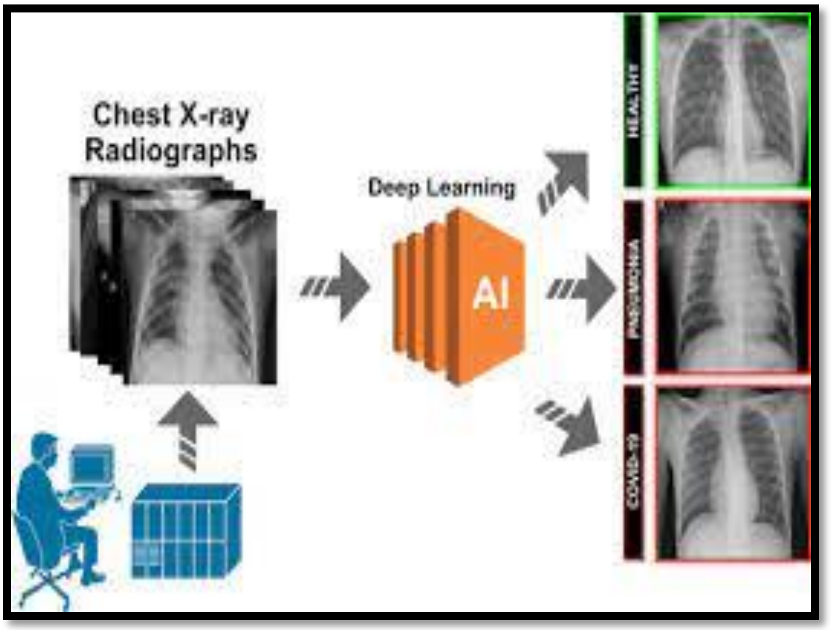

Fig – Detection of viruses

Objective of Dessertation

Our objective in this project is to create an image AI based model that can predict Chest X-Ray scans that belong to one of the three classes with a reasonably high accuracy.

Literature Survey:

1]João Victor S. das Chagas,1 Douglas de A. Rodrigues,1 Roberto F. Ivo,1 Mohammad Mehedi Hassan, 2 Victor Hugo C. de Albuquerque,3,4 and Pedro P. Rebouças Filho “This work proposes a method using CNNs as extractors of image characteristics and classic classifiers in a real-time IoT system to aid in the diagnosis of pneumonia in children. An extensive comparison of the method was carried out with twelve CNNs combined with seven classifiers equally tested on 1,200 CXR images of children”.

2]Shubham Chaudhary, Sadbhawna, Vinit Jakhetiya, Badri N Subudhi, Ujjwal Baid† , Sharath Chandra Guntuku† in 2021In this work, we proposed a two-stage framework to detect COVID-19 and CAP using CT scan images. In the first stage, individual slices of CT scans are labeled using fine-tuned DenseNet based deep-learning architecture. In the second stage, a fine-grained differential classification in three classes, i.e., COVID-19, CAP, and healthy individuals, by fine-tuning the EfficientNet architecture. The proposed two-stage framework achieved over 94% accuracy for classifying the CT scan images in the binary classification task: infectious vs. noninfectious, and accuracy of 89.3% for the fine-grained threeclass classification: COVID-19, CAP, and normal. Code and model weights are available at https://github.com/shubhamchaudhary2015/ct_covid19_cap_cnn.

3] Feng Shi, Liming Xia, Fei Shan, Dijia Wu, Ying Wei, Huan Yuan, Huiting Jiang, Yaozong Gao, He Sui, Dinggang Shen "China. In conclusion, CT imaging demonstrates high accuracy through machine learning technique and thus could be an efficient tool for COVID-19 screening. The infection size bias needs to be considered in both the method development and the result evaluation process".

4]Hanan Farhat, George E. Sakr, and Rima Kilany "As choosing the datasets is critical for training models, and over-fitting is probable especially with the varying imaging technologies and the wide variety of diseases, research is missing the third world population that might formulate different imaging features and is of more need to technological aid, especially with the present shortage of health institutions, medical staff and PACs. Unsupervised learning can thus be the solution, even though training data is becoming more relevant. It is early to have public datasets fully satisfying the needs of deep learning models, particularly for developing countries, but promising contributions can be expanded to different image modalities and populations, as in which do self-supervised learning covering segmentation and classification in 2D and 3D versions can be expanded."

5]Brent D. Davis,1, * Dawn Estes McKnight,2 Daniela Teodorescu,2 Anabel Quan-Haase,3,4 Rumi Chunara,5,6 Alona Fyshe,2,7 and Daniel J. Lizotte. We have presented a framework and case study that examines language on social media that is associated with discourse about depression. Rather than relying on manual categorisation of content and users, our approach leverages publicly available social media data from a community that discusses depression. From this, we generate both a set of keywords associated with depression discourse and a score that indicates how prevalent this discourse is over time.

6] Rodrigo Olivares 1, *, Roberto Munoz 1, *, Ricardo Soto 2, Broderick Crawford 2, Diego Cárdenas 1 , Aarón Ponce 1 and Carla Taramasco 1 Parkinson's Disease is a degenerative disorder of the central nervous system and it is the most common movement disorder diseases. Its diagnosis is frequently difficult especially when it is at an early stage. An early indication of patients suffer the Parkinson's Disease is the vocal impairment. Recent works have proposed mechanics to support the diagnosis task. In this paper, we propose an optimized ELM through the bio-inspired algorithm to properly classify patients with Parkinson's Disease. The approximate method defines an optimal vector with input weights and biases values, at the same time. The idea is optimizing the training phase of the ELM to generate the best classification model. To solve this problem, we first propose the bat algorithm to compute the parameter values in order to find the best attainable configuration for the ELM, and then, we test this proposal on voice signals in patients with Parkinson's Disease.

7]Vikash Chouhan 1 , Sanjay Kumar Singh 1 , Aditya Khamparia 1 , Deepak Gupta 2 , Prayag Tiwari 3 , Catarina Moreira 4 , Robertas Damaševiˇcius 5,* and Victor Hugo C. de Albuquerque 6 In this article, our goal is to propose a deep learning-based approach to classify pneumonia from chest X-ray images using transfer learning. In this framework, we adopted the transfer learning approach and used the pretrained architectures, AlexNet, DenseNet121, Inception V3, GoogLeNet and ResNet18 trained on the ImageNet dataset, to extract features. These features were passed to the classifiers of respective models, and the output was collected from individual architectures.

8]Mohammad Rahimzadeh, Abolfazl Attar "In this paper, we presented a concatenated neural network based on Xception and ResNet50V2 networks for classifying the chest X-ray images into three categories of normal, pneumonia, and COVID-19. We used two open-source datasets that contained 180 and 6054 images from patients infected to COVID-19 and pneumonia, respectively, and 8851 images from normal people. As we had a few images of COVID-19 class, we proposed a method for training the neural network when we the dataset is unbalanced. We separated the training set into 8 successive phases, in which there were 633 images (149 COVID-19, 234 pneumonia, 250 normal) in each phase. We selected the number of each class almost equal to each other in each phase so that our network also learns COVID-19 class characteristics, not only the other two class features. In each phase, the images from normal and pneumonia classes were different so that the network can distinguish COVID-19 from other classes better. between five folds. We hope that our trained network that is publicly available be helpful for medical diagnosis. We also hope that in the future, larger datasets from COVID-19 patients become available, and by using them, the accuracy of our proposed network increases for good".

9]Chuansheng Zheng, Xianbo Deng, Qiang Fu, Qiang Zhou, Jiapei Feng, Hui Ma, Wenyu Liu, Xinggang Wang "In conclusion, without the need for annotating the COVID-19 lesions in CT volumes for training, our weakly-supervised deep learning algorithm obtained strong COVID-19 detection performance. Therefore, our algorithm has great potential to be applied in clinical application for accurate and rapid COVID19 diagnosis, which is of great help for the frontline medical staff and is also vital to control this epidemic worldwide."

10] Ghaderzadeh et al. in their systematic review analyzed papers published between 1 November 2019, and 20 July 2020 regarding the application of deep learning (DL) in chest X-ray and CT. In this review, they suggested that DL-based models share high accuracy in the detection and diagnosis of COVID-19 and that the application of DL reduces false-positive and negative errors compared to radiological examination performed by a radiologist [16].

11] Shi et al. focused on the role of AI in chest CT and CXR in COVID-19 affected patients. They gave an overview of the whole pipeline regarding the implementation of DL in chest imaging, from image acquisition, segmentation to diagnosis, giving also insights regarding the follow-up and the public datasets available.

12]Sahlol et al. used an efficient hybrid classification which adopted a combination of CNN and an improved swarm-based feature selection algorithm. This combination should achieve two main targets; high performance and resource consumption, storage capacity. In addition, they also proposed a novel robust optimizer called Fractional-order Marine Predators Algorithm (FO-MPA) to efficiently select the huge feature vector produced from the CNN. Then, they tested and evaluated the proposed approach by performing extensive comparisons to several state-of-art feature selection algorithms, most recent CNN architectures and most recent relevant works and existing classification methods of COVID-19 images.

13]Li et al. also found that the severity scores were significantly associated with intubation/death within 3 days from the admission, in CXR rated moderate or severe [59].

14], Zhang et al. analyzed images from 2460 patients using the uAI Intelligent Assistant Analysis System (a modified 3D CNN and a combined V-Net with bottle-neck structures) to segment anatomical lung structures and to accurately localize infected regions, according to the specific lobes and segments. Their findings were consistent with those of previous studies [76] that demonstrate a typical bilateral involvement, mainly in the dorsal segments, with GGOs as the most common CT feature [77].

15]Saood et al. proposed a new fully automated deep learning framework for rapid quantification and differentiation between lung lesions in COVID-19 pneumonia on both contrast and non-contrast CT images using convolutional Long Short-Term Memory (ConvLSTM) networks. They showed a strong agreement between expert manual and automatic segmentation for lung lesions; describing excellent correlations of 0.978 and 0.981 for ground-glass opacity and high opacity volumes [87].

Research Methodology:

1. The COVID-19 Detection System

This section covers the methodology that was adopted in the development of the platform. It includes detailed explanation of the architecture, defines each block and its aspects, and demonstrates the followed evaluation measurements and calibration metrics.

One of the main challenges in every health-care system is the limited resources The availability and quality of data determine the reliability of the study and quality of the architecture. Using CT images requires a large dataset to ensure the aforementioned influences of data availability. Therefore, a large dataset was deployed in this study, consisting 6,752 CT scans We are proposing an AI-based medical hub platform that integrates AI and image processing for early detection of different problematic medical conditions. This platform targets medical problems that involve medical imaging. It provides the detection of abnormalities and classifies them accordingly. For the purpose of this work, we are targeting COVID-19 as a priority medical condition.

2. BLOCK DIAGRAM

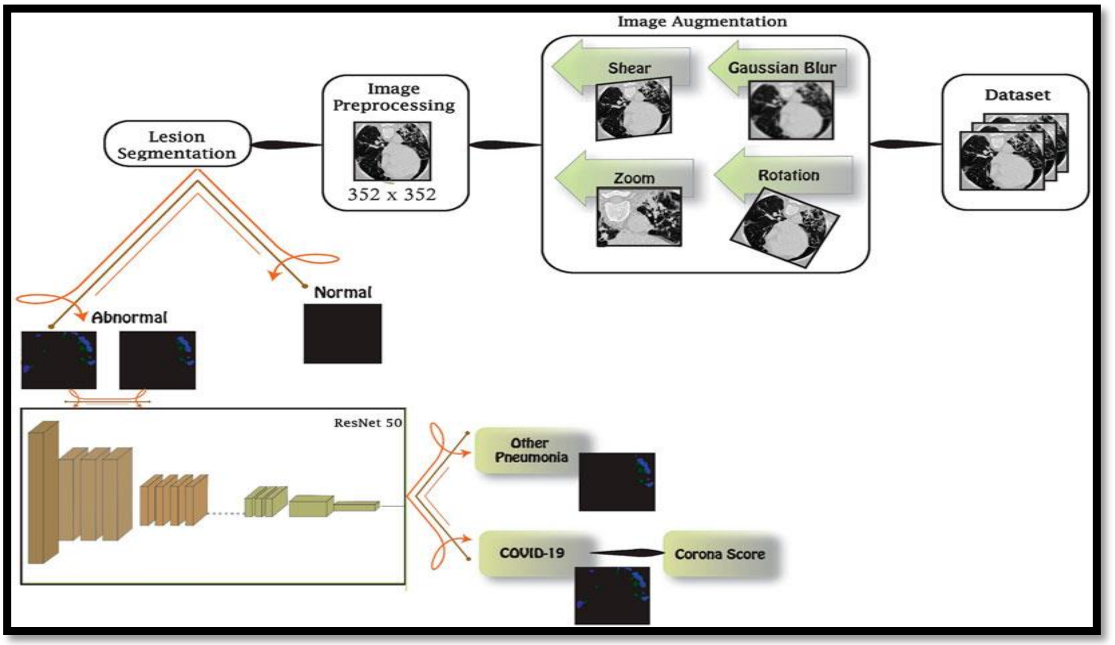

Fig – Block diagram of viruses' detection

First, the data are augmented to enrich the latter blocks with more images and to highlight special features to be recognized. This is done by rotating, shearing, zooming, and blurring images. Then, augmented data are preprocessed in two stages: standardization and normalization. These stages are essential to unify the data fed to the network. In order to identify abnormalities in images, the preprocessed images are fed into the lesion segmentation block that uses InfNet to treat abnormal aspects and features. In addition to early detection using this block, we are enabling it to detect the condition severity through further image analysis. Finally, the abnormal images are loaded into a deep network using the transfer learning method in order to distinguish between COVID-19 and other viral pneumonia conditions. Detailed information on each block will be elaborated in the following sections.

3. Image Augmentation

Data augmentation is a method used to yield extra data from the current dataset. It creates perturbed copies of the existing images, in this case. The main goal is to reinforce the neural network with various diversities, which leads to a network that distinguishes relevant from irrelevant characteristics in the dataset. Image augmentation can be done using several techniques. Augmentation techniques are used efficiently when necessary, according to data availability and quality. Our proposal integrates multiple techniques, to support a large number of datasets for different conditions, as follows:

- Rotation: the image is rotated within an interval between −10° and 10°.
- Zoom: scaling the image by zooming in or out would also increase the set.
- Shear: image shearing can be performed using rotation with the third-dimension imitation factor.

- Gaussian blur: using a Gaussian filter, high-frequency factors can be eliminated, causing a blurred version of an image.

Using these methods, the dataset was enlarged and used in the training phase. Nevertheless, during the testing phase, the testing set will not be augmented. This would assert the robustness of the architecture and avoid over-fitting.

4. Image Preprocessing

Since the data typically come from various origins, a strategy to guide the complexity and accuracy is essential. Image preprocessing ensures complexity reduction and better accuracy yielded from certain data. This method standardizes the data through several stages in order to feed the network with a clean dataset. In this architecture, data preprocessing is performed through the following stages:

- Image standardization: neural networks that deal with images need unified aspect ratio images. Therefore, the first step is to resize the images into unique dimensions and a square shape, which is the typical shape used in neural networks.
- Normalization: input pixels to any AI algorithm must have normalized data distribution to enhance the convergence of the training phase. Normalization is the action of subtracting the mean of the distribution from each pixel and dividing by standard deviation. To achieve positive values, scaling normalized data is considered at the end of this step.

5. Lesions' Segmentation

Ground glass opacities (GGOs) and consolidation are the main extracted features in the case of COVID-19 patients, where 97.86% of patients have such infections within 21 days of the presence of COVID-19. Therefore, we used lesions' segmentation to identify the existence of these infections and the infected volume. These infections are also caused by other viral pneumonia, so this block will classify an input image as normal or abnormal. Normal ones are released as output, while abnormal ones will enter the ResNet block in order to identify COVID-19 patients. The segmentation method uses the architecture of InfNet.

The preprocessed data consisting of CT images will undergo the famous split ratio mentioned by the Pareto principle. 80% of the images will be considered in the training process, while 20% of the dataset will be used in testing the network.

The preprocessed CT images are fed into two convolutional layers where low-resolution features are extracted. Then, these features are inserted into three convolutional layers to extract the high-level ones. In the context of segmentation, it was shown that edge information can be beneficial, and thus, an edge attention unit is placed to enhance the demonstration of regions of interest.

Global map is produced by accumulating the high-level features using a parallel partial decoder to segment the lung lesions. The output and high-level features are joined with low-level features to be inserted in cascaded reverse attention units based on the global map. Finally, the output is inserted into an activation function

(Sigmoid) to estimate the regions of infections.

This block segments the infected sections in a CT-scan image to create a colored representation of the GGO and consolidation segment. The absence of such sections will result in a blank black image. Blank images are classified as normal. The rest of the abnormal images are fed to the ResNet50 deep network model. These representations are also quantified to be used later in calculating the corona score.

6. ResNet50 Deep Network

Transferring learning is a well-known method that can be used to train convolutional neural networks as it occupies a huge space within the literature. Using this method, the network is pretrained based on a vast database known as ImageNet. This step leads to the initialization of the layers' weights where loading such weights before deploying the network in the current architecture diminishes the vanishing gradient problem. This is a key advantage for transfer learning that enhances the convergence of the objective. Another advantage using this type of learning is to extract relevant features of the images, such as shape and edges. As a result, the computational time is reduced by limiting the computations to the final layers in the training procedure.

The residual network ResNet is one of the advanced deep learning algorithms that surpass many other dense networks in various metrics, especially accuracy and computational complexity .This is why we used this algorithm for detecting the coronavirus and distinguishing it from other viral pneumonia infections using transfer learning.

In order to identify the dataset through numerous classes, the pretrained model characterizes the last layers as classification layers, and thus, the extracted features will be saved in the last convolutional layer to be transformed into prediction values for each class. The initialized weights (the fundamental factor of transfer learning methods) do not change, except for the last layer, which will be trained to produce estimates, which leads the classification process for our new set of images. Other layers are inserted into this model like the pooling layer, dropout layer, flattening layer, and the activation functions (rectified linear unit).

The residual network used in this architecture consists of 50 layers, ResNet50 , which is a deep network that considers the learning rate as an assessment in the stage to adapt the weights of the layers. In each iteration, the weights are updated based on the loss derived from the input and expected values. The formula of the updated weights is as follows:

7. The Proposed CNN Model

The CNN model used in the present study has two major sections: feature extractors and classifiers. A CNN model uses a hierarchical model that functions to create a network and produces a fully connected layer resembling neurons connected to each other; therefore, this model generates the most efficient results in the classification of images with fewer errors. Figure 3 shows a general CNN architecture used in the present study.

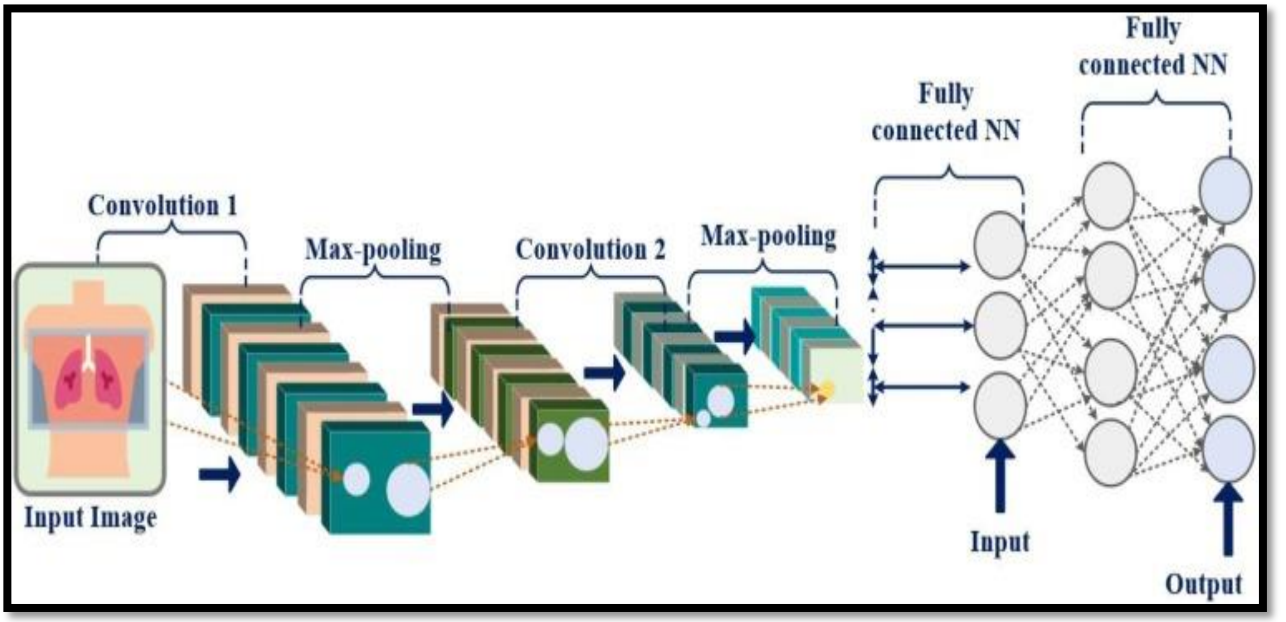

Fig – Working of image processing

Conclusion:

In this project, we proposed an advanced medical hub architecture with an AI system that consists of two phases: segmentation and ResNet deep network. The first phase is responsible of recognizing abnormalities in the CT images to separate normal from abnormal patients. The second one is responsible of distinguishing COVID-19 cases from other pneumonia conditions. Both phases showed promising performances. The accuracy of the segmentation was 95.54 and 96.5% for the ResNet50 block. The overall accuracy proved to be 95%. The whole model showed to be reliable and demanded much less computational time, since better convergence was achieved due to the presence of the segmentation block. Our study also introduced an evaluation score for the severity of COVID-19 cases (corona score). Even minimal severity can be detected, which could initiate an instantaneous quarantine decision to avoid the spread of the virus. This platform concentrated on the detection COVID-19 in the current study, but it can be deployed and used for medical imaging analysis of other diseases.

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