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COVID – 19 PREDICTION MODEL USING DEEP LEARNING

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ABSTRACT

Coronavirus Disease (COVID19) is a fast-spreading infectious disease that is currently causing a healthcare crisis around the world. Due to the current limitations of the reverse transcription-polymerase chain reaction (RT-PCR) based tests for detecting COVID19, recently radiology imaging based ideas have been proposed by various works. Computed Tomography (CT) imaging plays a critical role for detection of manifestations in the lung associated with COVID-19, where segmentation of the infection lesions from CT scans is important for quantitative measurement of the disease progression in accurate diagnosis and follow-up assessment. In this projectwe use Convolution Neural Network to predict the COVID19 disease in the given chest CT scan images. It is an automated detection of lung infections from computed tomography (CT) images offers a great potential to augment the traditional healthcare strategy for tackling COVID-19.

I.INTRODUCTION

1.1 COVID -19

Coronaviruses are a large family of viruses which may cause disease in animals or humans. Seven coronaviruses can produce infection in people around the world but commonly people get infected with these four human coronaviruses: 229E, NL63, OC43, and HKU1. They usually cause a respiratory infection ranging from the common cold to more severe diseases such as Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS) and themost recently discovered coronavirus (COVID-19) cause‟s infectious disease. This zoonotic disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2).

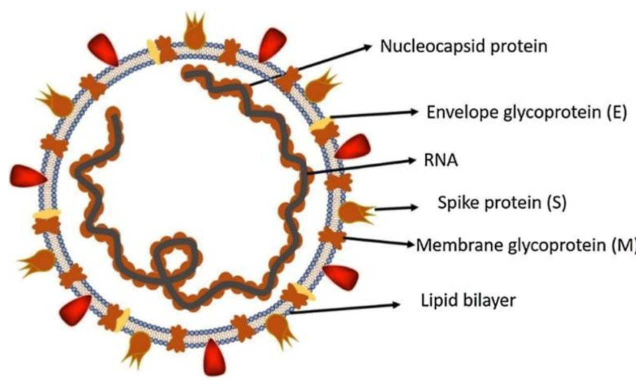

Figure 1.1 A structure of Respiratory Syndrome (SARS) coronavirus

The WHO originally called this infectious disease Novel Coronavirus-Infected Pneumonia (NCIP) and the virus had been named 2019 novel coronavirus (2019-nCoV). On 11th Feb 2020, the (WHO) officially renamed the clinical condition COVID-19 (a shortening of Corona Virus Disease-19), which was announced in a tweet. An outbreak of COVID-19 caused by the 2019 novel coronavirus (SARS-CoV-2) began in Wuhan, Hubei Province, China in December 2019, the current outbreak is officially a pandemic. Since knowledge about this virus is rapidly evolving, readers are urged to update

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themselves regularly (Fig. 1.1).

The virus is typically rapidly spread from one person to another via respiratory droplets produced during coughing and sneezing. It is considered most contagious when people are symptomatic, although transmission may be possible before symptoms show in patients. The standard tool of diagnosis is by reverse transcription polymerase chain reaction (rRT-PCR) from a throat swab or nasopharyngeal swab. The infection can also be diagnosed from a combination of symptoms, risk factors and a chest CT scan showing features of pneumonia.

1.1.1 Origin and Transmission of COVID-19

The first cases of coronaviruses in human found in 1965 by Tyrrell and Bynoe. They observed that they could passage a virus named B814. It was observed in human embryonic tracheal organ cultures obtained from the respiratory tract of an adult with a common cold symptom. The first cases were seen in Wuhan City of Hubei Province China in December 2019, and have been linked to the Huanan Seafood Market (South China) and the infection has spread to several countries around the world.

The novel coronavirus originated from the Hunan seafood market at Wuhan, South China where raccoon dogs, bats, snakes, palm civets, and other animals are sold, and rapidly spread up to 109 countries. The zoonotic source of SARS CoV-2 is not confirmed, however, the sequence-based analysis suggested bats as the main reservoir. The recombination of DNA was found to be involved at spike glycoprotein which assorted SARS-CoV (CoVZXC21 or CoVZC45) with the RBD of another Beta CoV, thus could be the reason for cross-species transmission and rapid infection. The virus that causes coronavirus disease 19 (COVID-19) is a highly transmittable and pathogenic viral infection and mainly transmitted through contact with respiratory droplets rather than through the air.

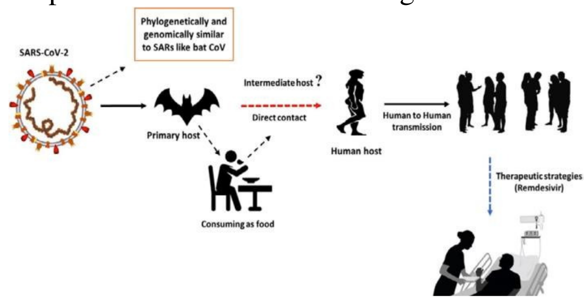
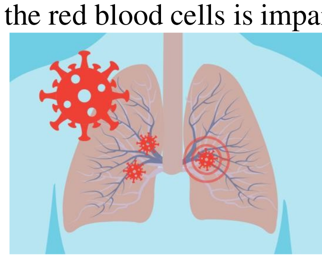


Figure 1.2. Transmission of COVID-19 to human host.

Primarily people can catch coronavirus disease 19 (COVID-19) from others who are infected. A single cough can circulate up to 3.000 droplets. These droplets can land on other people, and covering surfaces around them, however, several smaller particles will stay within the air. Transmission of COVID-19 is shown in Figure 1.2.

1.1.2 Effect of COVID 19 on lungs

COVID-19 is a respiratory disease, one that especially reaches into your respiratory tract, which includes your lungs. COVID-19 can cause a range of breathing problems, from mild to critical. COVID 19 directly impacts the lungs and damages the alveoli (tiny air sacs). The function of the alveolus is to transfer oxygen to the blood vessels. These blood vessels or capillaries carry the oxygen to the RBCs (Red blood cells). It is the RBCs that finally deliver the oxygen to all the internal organs in the body. The virus works by damaging the wall and the lining of the alveolus and capillaries (Fig 1.4). The debris from the damage, which is plasma protein accumulates on the alveolus wall and thickens the lining. As the walls‟ thicken, the transfer of oxygen to the red blood cells is impaired.



1.3 Coronavirus in Lungs

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The thicker the wall gets, the more difficult it gets to transfer oxygen to the red blood cells, which causes difficulty in breathing as the body is running short of oxygen. And the lack of oxygen to the internal organs results in a deficit in the body and impairs the functioning of the organs. At this juncture, the body fights to increase oxygen intake. And the first response of the body is to destroy the virus and prevent its replication, but if the individual has weaker immunity then the body is unable to stop the virus, and this aggravates the crisis. Medical imaging like X-ray and computed tomography (CT) of lungs can play an important role in the early prediction of COVID-19 patients that will help the timely treatment of the patients.

1.2 ABOUT THE PROJECT

COVID-19 pandemic is widely spreading over the entire world and has established significant community spread. Raising a prediction system can help prepare the officials to respond properly and quickly. Medical imaging like X-ray and computed tomography (CT) of lungs of COVID-19 patients can help to detect the impact of COVID-19 virus in patients.

Automate diagnosis of patients from radiological features is possible to lessen the burden of medical staff and increase their efficacy. Deep learning techniques have proven fruitful for disease detection. This project "COVID-19 Deep Learning Prediction Model Using Convolutional Neural Network" aims at devising a Convolutional Neural Network (CNN) based model that can classify the patients into COVID-19 and normal pneumonia patients using CT images.

A CNN based Deep Learning model is proposed that can classify the patients into COVID-19 based on the CT scan images.

- The proposed approach is tested for Normal and infected samples of CT scan images.
- Image preprocessing steps are defined that can help in edge detection and segmentation of the infected area and thus increase the accuracy of the proposed model.
- An open dataset of COVID-19 patients containing CT scan images is utilized to evaluate the performance of the proposed model and the results are compared with unit and mixed deep learning approaches.

II. LITERATURE SURVEY

2.1. "Review of Artificial Intelligence Techniques in Imaging Data Acquisition, Segmentation and Diagnosis for COVID-19"Author name: F. Shi, J. Wang Year: 2020

The pandemic of coronavirus disease 2019 (COVID-19) is spreading all over the world. Medical imaging such as X-ray and computed tomography (CT) plays an essential role in the global fight against COVID-19, whereas the recently emerging artificial intelligence (AI) technologies further strengthen the power of the imaging tools and help medical specialists. AI-empowered image acquisition can significantly help automate the scanning procedure and also reshape the workflow with minimal contact to patients, providing the best protection to the imaging technicians. Also, AI can improve work efficiency by accurate delineation of infections in X-ray and CT images, facilitating subsequent quantification. Moreover, the computer-aided platforms help radiologists make clinical decisions, i.e., for disease diagnosis, tracking, and prognosis.

2.2. "Unsupervised CT lung image segmentation of a mycobacterium tuberculosis infection model"Author name: P. M. Gordaliza, A. Munoz-Barrutia, M. AbellaYear: 2018

Tuberculosis (TB) is an infectious disease caused by Mycobacterium tuberculosis that produces pulmonary damage. Lung segmentation is the step before biomarker extraction. In this study, present an automatic procedure that enables robust segmentation of damaged lungs that have lesions attached to

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the parenchyma and are affected by respiratory movement artifacts in a Mycobacterium Tuberculosis infection model. Its main steps are the extraction of the healthy lung tissue and the airway tree followed by elimination of the fuzzy boundaries. Its performance was compared with respect to a segmentation obtained using: (1) a semi-automatic tool and
(2) an approach based on fuzzy connectedness. A consensus segmentation resulting from the majority voting of three experts‟ annotations was considered our ground truth.

2.3. "Central focused convolutional neural networks: Developing a data-driven model for lung nodule segmentation"Author name: S. Wang, M. ZhouYear: 2017

Accurate lung nodule segmentation from computed tomography (CT) images is of great importancefor image-driven lung cancer analysis. In this study, propose a data-driven model, termed the Central Focused Convolutional Neural Networks (CF-CNN), to segment lung nodules from heterogeneous CT images. This approach combines two key insights: 1) the proposed model captures a diverse set of nodule-sensitive features from both 3-D and 2-D CT images simultaneously; 2) when classifying an image voxel, the effects of its neighbor voxels can vary according to their spatial locations. This phenomenon by proposing a novel central pooling layer retaining much information on voxel patch center, followed by a multi-scale patch learning strategy. Moreover, a weighted sampling to facilitate the model training, where training samples are selected according to their degree of segmentation difficulty.

2.4. "Multiple resolution residually connected feature streams for automatic lung tumor segmentation from CT images"Author name: J. Jiang, Y.-C. HuYear: 2018

Volumetric lung tumor segmentation and accurate longitudinal tracking of tumor volume changes from computed tomography (CT) images are essential for monitoring tumor response to therapy. Hence developed two multiple resolution residually connected network (MRRN) formulations called incremental-MRRN and dense-MRRN. This networks simultaneously combine features across multiple image resolution and feature levels through residual connections to detect and segment lung tumors. It consists of two different multiple resolution residual network (MRRN) called the incremental and dense MRRN. Feature map input in each residual stream is produced through pooling (for dense MRRN) and followed by convolutions with residual connections (for the incremental MRRN). Additionally, the feature maps in each residual stream are refined as they are combined with subsequent layers.

2.5. "Unsupervised anomaly detection with generative adversarial networks to guide marker discovery"Author name: T. Schlegl, P. Seeb¨ockYear: 2017

Obtaining models that capture imaging markers relevant for disease progression and treatment monitoring is challenging. Models are typically based on large amounts of data with annotated examples of known markers aiming at automating detection. Here, performed unsupervised learning to identify anomalies in imaging data as candidates for markers. AnoGAN, a deep convolutional generative adversarial network to learn a manifold of normal anatomical variability, accompanying a novel anomaly scoring scheme based on the mapping from image space to a latent space. Applied to new data, the model labels anomalies, and scores image patches indicating their fit into the learned distribution.

III. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

In this section, three types of works that are most related to our work is discussed which includes segmentation in chest CT, semi supervised learning, and Deep Learning

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approach for COVID-19.

Segmentation in Chest CT

CT imaging is a popular technique for the diagnosis of lung diseases. In practice, segmenting different organs and lesions from chest CT slices can provide crucial information for doctors to diagnose and quantify lung diseases. Recently, many works have been provided and obtained promising performances. These algorithms often employ a classifier with extracted features for nodule segmentation in chest CT. For example, utilized the support vector machine (SVM) classifier is to detect the lung nodule from CT slices.

An automated lung segmentation system is based on bidirectional chain code to improve the performance. However, the similar visual appearances of nodules and background makes it difficult for extracting the nodule regions. To overcome this issue, several deep learning algorithms have been proposed to learn a powerful visual representation. For instance, developed a central focused convolutional neural network to segment lung nodules from heterogeneous CT slices. Utilized GAN-synthesized data to improve the training of a discriminative model for pathological lung segmentation. Designed two deep networks to segment lung tumors from CT slices by adding multiple residual streams of varying resolutions. An explainable COVID-19 diagnosis system is by joint classification and segmentation.

3.1.1. Annotation-Efficient Deep Learning

This approach segments the COVID-19 infection regions for quantifying and evaluating the disease progression. The (unsupervised) anomaly detection/segmentation could detect the anomaly region, however, it cannot identify whether the anomaly region is related to COVID-19. By contrast, based on the few labeled data, the semi-supervised model could identify the target region from other anomaly region, which is better suit for assessment of COVID-19. Moreover, the transfer learning technique is another good choice for dealing with limited data. The major issue for segmentation of COVID-19 infection is that there are already some public datasets, but, being short of high quality pixel-level annotations. This problem will become more pronounced, even collecting large scale COVID-19 dataset, where the annotations are still expensive to acquire. Thus to utilize the limited annotation efficiently and leverage unlabeled data, Semi-supervised learning provides a more suitable solution to address the issue. This approach may not be sufficient for a completely automated prediction system.

3.2 PROPOSED SYSTEM

A novel COVID-19 optimized Lung Infection Segmentation Deep Network is proposed to automatically identify infected regions from chest CT slices. At first we are collected large number of CT scan images of COVID-19 Patients and Normal Persons, then we train the Machine by using Convolution Neural Network (CNN) with the COVID-19 and Normal CT scan Images, so that the machine can able to identify the features of normal CT images and COVID-19 CT images.

3.2.1 Deep Learning

Deep learning (also known as deep structured learning) is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised. Deep learning is a well-known research area in artificial intelligence.

Deep learning architectures such as deep neural networks, deep belief networks, recurrent neural networks and convolution neural networks have been applied to fields

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including computer vision, machine vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance.

The adjective "deep" in deep learning comes from the use of multiple layers in the network. Early work showed that a linear perceptron cannot be a universal classifier, and then that a network with a non-polynomial activation function with one hidden layer of unbounded width can on the other hand so be. Deep learning is a modern variation which is concerned with an unbounded number of layers of bounded size, which permits practical application and optimized implementation, while retaining theoretical universality under mild conditions. In deep learning the layers are also permitted to be heterogeneous and to deviate widely from biologically informed connectionist models, for the sake of efficiency, trainability and understandability, whence the "structured" part.

3.2.2 Convolutional Neural Network

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery.[1] They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics.[2][3] They have applications in image and video recognition, recommender systems,[4] image classification, medical image analysis, natural language processing,[5] and financial time series.[6]

CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "fully-connectedness" of these networks makes them prone to overfitting data. Typical ways of regularization include adding some form of magnitude measurement of weights to the loss function. CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble more complex patterns using smaller and simpler patterns.

Through Deep learning with CNN model high prediction score is obtained. This technique is applied in assessing the diagnosis of COVID-19, e.g., quantifying the infected regions and monitoring the longitudinal disease changes. The proposed system is implemented using python (Tensor flow library). This approach provides promising results with end to end modeling without manual feature engineering in medical image classification.

IV DEEP LEARING WITH PYTHON LIBRARIES

Deep Learning is becoming a very popular subset of machine learning due to its high level of performance across many types of data. A great way to use deep learning to classify images is to build a convolutional neural network (CNN). The Keras library in Python makes it simple to build a CNN. Computers see images using pixels. Pixels in images are usually related.

For example, a certain group of pixels may signify an edge in an image or some other pattern. Convolutions use this to help identify images. A convolution multiplies a matrix of pixels with a filter matrix or „kernel‟ and sums up the multiplication values. Then the convolution slides over to the next pixel and repeats the same process until all the image pixels have been covered.

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4.2.1 KERAS & TENSOR FLOW LIBRARIES

KERAS is an Open Source Neural Network library written in Python that runs on top of Tensorflow. It is designed to be modular, fast and easy to use. It was developed by François Chollet, a Google engineer. It is a useful library to construct any deep learning algorithm.Steps includes Loading the Data set, Building a model, Compiling the Model, Training the Model and using the model to make predictions

Packages

*from tensorflow.keras.layers import **
*from tensorflow.keras.models import **
from tensorflow.keras.preprocessing import image

V. SYSTEM ARCHITECTURE

5.1 METHODOLOGY

A novel COVID-19 optimized Lung Infection Segmentation Deep Network is proposed to automatically identify infected regions from chest CT slices. At first we are collected large number of CT scan images of COVID-19 Patients and Normal Persons, then we train the Machine by using Convolution Neural Network (CNN) with the COVID-19 and Normal CT scan Images, so that the machine can able to identify the features of normal CT images and COVID-19 CT images. Through this we can able to get high prediction score. This technique is applied in assessing the diagnosis of COVID-19.Automate diagnosis of patients from radiological features is possible to lessen the burden of medical staff and increase their efficacy. Deep learning techniques have proven fruitful for disease detection.

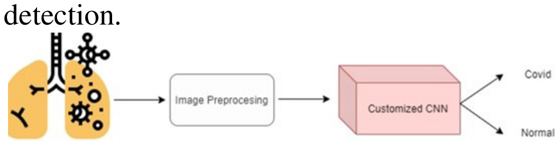

Fig. 5.1 Architecture of the proposed approach

5.2 DEEP LEARNING

Deep learning (also known as deep structured learning) is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi or unsupervised. Deep learning architectures such as deep neural networks, deep belief networks, recurrent neural networks and convolution neural networks have been applied to fields including computer vision, machine vision, speech recognition, natural language processing, audio recognition, social network iltering, machine translation, bioinformatics, drug design, medical image analysis and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance. Deep learning is a modern variation which is concerned with an unbounded number of layers of bounded size, which permits practical application and optimized implementation, while retaining theoretical universality under mild conditions. In deep learning the layers are also permitted to be heterogeneous and to deviate widely from biologically informed connectionist models, for the sake of efficiency, trainability and understandability, whence the "structured" part.

Deep learning is a well-known research area in artificial intelligence. It provides promising results with end to end modeling without manual feature engineering in medical image classification.

5.3.1 PREPROCESSING

A pre-processing or filtering step is applied to minimize the degradation related to the noise. There has been a lot of work in structuring the efficient noise suppression filters. The noise such as the shadow in the input images are removed using the pre-processing filters such as average filter. This stage is necessary to

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enhance the lungs image quality and made the feature extraction component more reliable for the improvement of broad and narrow input image.

The preprocessing aims at removing the noise in images to improve the training process of CNN. Predominantly, input images are large which increases the training time. The first step is to reduce the size of the images. we need to reshape our dataset inputs (X_train and X_test) to the shape that our model expects when we train the model.

5.3.2 CONVOLUTIONAL NEURAL NETWORK

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery[1]. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation.variance characteristics.[2][3] They have applications in image and video recognition, recommender systems, [4] image classification, medical image analysis, natural language processing, [5] and financial time series.[6]

CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons

5.3 PROPOSED APPROACH

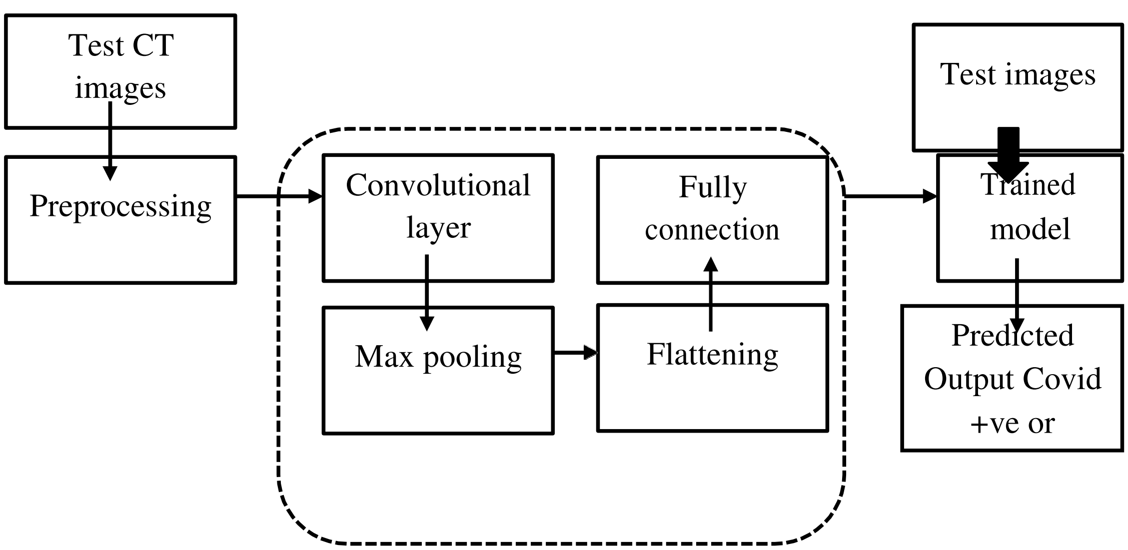

Fig.5.2. Proposed Block Diagram

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in the next layer. The "fully-connectedness" of these networks makes them prone to overfitting data. Typical ways of regularization include adding some form of magnitude measurement of weights to the loss function. CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble more complex patterns using smaller and simpler patterns. Therefore, on the scale of connectedness and complexity, CNNs are on the lower extreme.

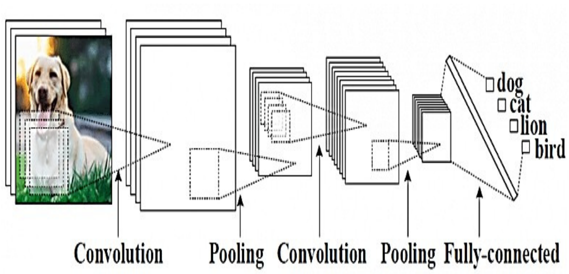

Fig. 5.3. Architecture of Convolutional neural network

The steps involved in CNN process is listed as Step 1: Convolution
Step 2: Max pooling Step 3: Flattening
Step 4: Fully connected

5.3.2.1 Convolution

When programming a CNN, the input is a tensor with shape (number of images) x (image height) x (image width) x (image depth). Then after passing through a convolutional layer, the image becomes abstracted to a feature map, with shape (number of images) x (feature map height) x (feature map width) x (feature map channels).

A convolutional layer within a neural network should have the following attributes:

- Convolutional kernels defined by a width and height (hyper-parameters).
- The number of input channels and output channels (hyper-parameter).
- The depth of the Convolution filter (the input channels) must be equal to the number channels (depth) of the input feature map.

Convolutional layers convolve the input and pass its result to the next layer. This is similar to the response of a neuron in the visual cortex to a specific stimulus.[12] Each convolutional neuron processes data only for its receptive field. Although fully connected feedforward neural networks can be used to learn features as well as classify data, it is not practical to apply this architecture to images. A very high number of neurons would be necessary, even in a shallow (opposite of deep) architecture, due to the very large input sizes associated with images, where each pixel is a relevant variable.

Convolutional neural networks (CNN) have been specifcally utilized for computer vision tasks. CNN comprises of a large number of convolutional, as well as, pooling and fully connected layers, each layer performing a different task. For example, the convolutional layer uses a fixed size filter called kernel to extract local features from the input image. A new convolved image is obtained each time a convolution is applied. Each convolved image contains features that have been extracted from the image of the previous step. Let I(x, y) be a 2D input image and let f(x, y) be the 2D kernel applied for convolution. When the convolution is applied, the pixel values at the edges can be ignored or padding can be applied. For instance, a fully connected layer for a (small) image of size 100 x 100 has 10,000 weights for each neuron in the second layer. The convolution operation brings a solution to this problem as it reduces the number of free parameters, allowing the network to be deeper with fewer parameters.[13] For instance, regardless of image size, tiling regions of size 5 x 5, each with the same shared weights, requires only 25 learnable parameters. By using regularized weights over fewer parameters, the vanishing gradient and exploding gradient problems seen during backpropagation in traditional neural networks are avoided.[14][15]

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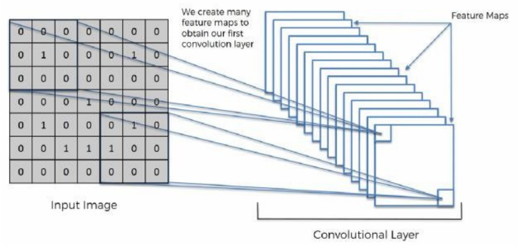

Fig 5.4 (a) Convolution Layers

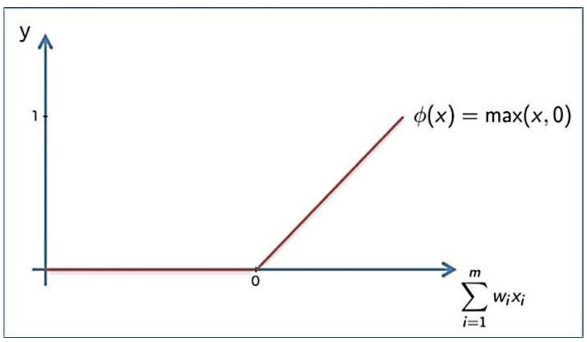

Fig 5.4. (b) Applying ReLu Activation function to decrease the linearity in the image, because the image originally nonlinear

#Training
model model
= Sequential()
 ## creating a blank model
model.add(Conv2D(32,kernel_size=(3,
3),activ
ation='relu',input_shape=(224,224,3))

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5.3.2.2 Pooling Layer

A **pooling** layer is another building block of a **CNN**. Its function is to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network. **Pooling** layer operates on each feature map independently. The most common approach used in **pooling** is max **pooling**.

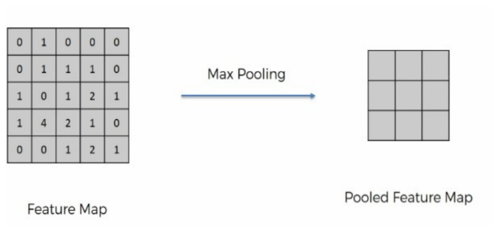

Fig.5.5. (a) Max Pooling

```
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(64,(3,3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))
```

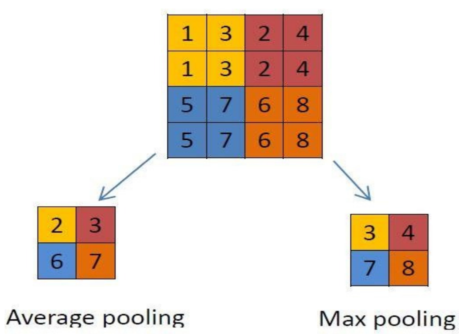

Fig.5.5. (b) Max / Avg. Pooling

5.3.2.3 Flattening

Flattening is converting the data into a 1-dimensional array for inputting it to the next layer. We **flatten** the output of the convolutional layers to create a single long feature vector. And it is connected to the final classification model, which is called a fully-connected layer. model.add(Flatten())

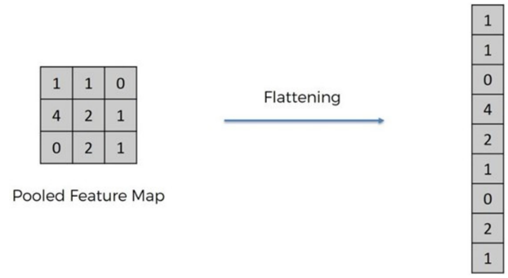

Fig. 5.6 (a) Flattening

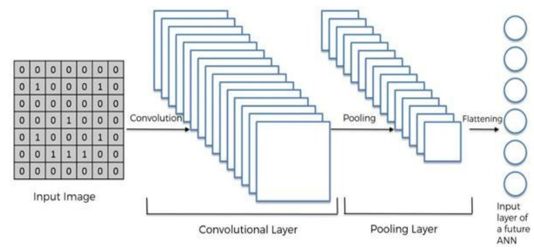

Fig. 5.6 (b) Flattening

5.3.2.4 Connectivity

Fully connected layers connect every neuron in one layer to every neuron in another layer. It is in principle the same as the traditional multi-layer perceptron neural network (MLP). The flattened matrix goes through a fully connected layer to classify the images.

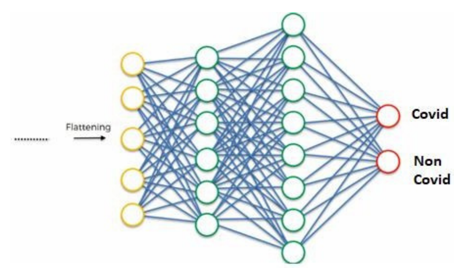

Fig. 5.7 Connectivity

5.4 DATA SET DESCRIPTION

CT images are high-quality 3D images achieved from tomography. CT images are 3D images and contain hundreds of slices. It requires a substantial amount of time and computational resources to preprocess these images before we can put them to the training models. CT images can give more accurate result rather than X-Ray images.

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This study uses the CT Scan image datasets from sources available at Kaggle (2020) and it contains 200 images of COVID-19 patients and 200 images for normal people.

Figure 5.8 shows a few sample images from the dataset. Further images are generated using Dataset-2 using the ImageDataGenerator class form Keras. The size of the training dataset can potentially influence the performance of deep learning models. Deep learning is a data intensive approach and requires a large amount of data for training. The smaller dataset of X-ray images is not appropriate to produce generalized results. Among the widely used methods are Keras ImageDataGenerator class.

VI. RESULTS & DISCUSSIONS

The proposed model is tested with images which involve two classes. Training and testing is performed with two classes, i.e., COVID-19 and Normal. The proposed model is trained and tested with 500 CT Scan images of COVID-19 and normal people combined for two classes.

A great way to use deep learning to classify images is to build a convolutional neural network (CNN). The Keras library in Python makes it simple to build a CNN. We have used CT Scan image datasets from sources available at Kaggle (2020) and it contains 200 images of COVID-19 patients and 200 images for normal people.

Accuracy is one of the widely used metric to evaluate a classifiers performance and is calculated using Precision and recall are among the commonly used metrics for classifier performance evaluation.

6.1 Accuracy

Accuracy is one metric for evaluating classification models. Informally, accuracy is the fraction of predictions our model got right. Formally, accuracy has the following definition:

Accuracy = Number of correct predictions /Total number of predictions

For binary classification, accuracy can also be calculated in terms of positives and negatives as follows:

Accuracy=(TP+TN) / (TP+TN+FP+FN)

Where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

Fig. 6.1(a) Training output – Mixed Model

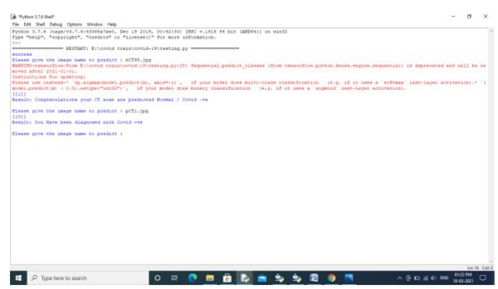

Fig. 6.1(b) Test Output

Fig. 6.1(c) Training output – Unet Model

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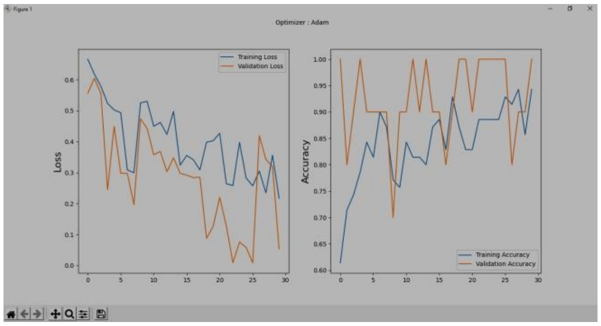

Fig 6.2 Validation and Training Accuracy and loss

VII. CONCLUSION AND FUTURE ENHANCEMENTS

In this project, we have proposed a novel COVID-19 lung CT infection segmentation network, named Convolutional Neural Network (CNN), which utilizes an implicit reverse attention and explicit edge-attention to improve the identification of infected regions. Our system has great potential to be applied in assessing the diagnosis of COVID-19, e.g., quantifying the infected regions, monitoring the longitudinal disease changes, and mass screening processing. This proposed model is able to detect the objects with low intensity contrast between infections and normal tissues.

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