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# **A Supervised Framework for COVID-19 Classification Using FCNN**

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## **ABSTRACT**

One or both of the lungs are affected by pneumonia, which is the enlargement of the lung tissue. Infection with organisms including bacteria, viruses, and fungi leads to its occurrence. Although its severity varies, its typical symptoms include coughing, breathing problems, fever, and chest pain. The respiratory illness COVID-19 is spreadable and is brought on by the SARS- CoV-2 virus. COVID-19 has similar symptoms to viral pneumonia and the patients of COVID-19 may also be subject to secondary bacterial infections. This study separates COVID-19 from other illnesses like mycoplasma, bacterial pneumonia, viral pneumonia, and other infections using a variety of deep learning techniques and computed tomography (CT) images. The results show that for all three cases, FCNN is one of the best performing architectures.

**Keywords:** Bacterial pneumonia, fully convolutional neural net- works, COVID-19, CT images, deep learning, mycoplasma pneumonia, viral pneumonia

## **1 Objective of Our Project**

Since Dec 2019, a large and increasing outbreak of a novel coronavirus was reported in Wuhan, Hubei province of China, which can cause acute respiratory illness and even fatal acute respiratory distress syndrome (ARDS). The new coronavirus was named as SARS-CoV-2 by International Committee on Taxonomy of Viruses (ICTV) and the infectious diseases infected by this coronavirus was named as Coronavirus Disease 2019 (COVID-19) by World Health Organization (WHO). The new coronavirus has been confirmed of human-to-human transmission, and due to the massive transportation and large population mobility before the Chinese Spring Festival, this new coronavirus has spread quickly to other parts of China with significant morbidity and mortality. According to the data from the National Health Commission of the People's Republic of China, update till 24 o'clock of Mar 29, 2020, China has reported 82447 identified cases with SARS-CoV-2, including 3,311 death cases; 82.2% (67,801/82,447) of the identified cases came from Hubei province and identified cases in Wuhan, the very center of epidemic area of Hubei province, accounted about 73.8%(50,006/67,801) of the data in Hubei province. Moreover, COVID-19 cases outside China have been reported in more than 200



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countries, areas or territories. According to the COVID-19 situation dashboard, a total of 638,146 confirmed cases with 30,039 deaths cases worldwide were reported as of March 29, 2020, at 18:00 Central European Time. In the World Health Organization (WHO) website. Countries with the most numbers of confirmed cases included United States of America with 103,321 cases, Italy with 92,472 cases, China with 82,356 cases, Spain with 72,248 cases, Germany with 52,547 cases, Iran with 38,309 cases, France with 37,145 cases and so on. With the tremendously fast spread of SARS-CoV-2, it has been declared to be a Public Health Emergency of International Concern (PHEIC) by WHO on 30 January 2020, and the global level of assessment of the risk of spread and the risk of impact of COVID-19 has been increased to be Very High by WHO on Feb 28, 2020 which poses a great threat to the international human health. Isolating the infected and immunizing the susceptible are crucial components in the control and eradication of COVID-19. The RT-PCR (Reverse Transcription Polymerase Chain Reaction) test is currently the gold standard for COVID-19 detection, although it takes longer to analyse the specimen and get the result. Also, it has been observed that many patients may test positive for COVID-19 after recovery [7]. People are known to become immune to the virus by vaccination, although they are still susceptible to infection. It will take a long time to develop a vaccination that is both safe and effective for a long time. Due to restrictions on the vaccine's availability and the population's geographic dispersion, immunization of the entire world's population will also take some time. Efforts are also being made to develop rapid diagnostic methods for COVID-19 identification using commonly examined CT and CXR images by radiologists. A skilled radiologist is required because manual diagnosis of COVID-19 is time-consuming. Early abnormalities of COVID-19 may resemble those of other pulmonary syndromes like Severe Acute Respiratory Syndrome (SARS) or Viral Pneumonia (VP), which can also obstruct the timely diagnosis and treatment of COVID, it is also necessary to have access to a skilled radiologist. Examples of CXR and CT scans of COVID and non-COVID instances are displayed in Figures 2 and 3, respectively. Bilateral dispersed ground-glass is visible in the axial pictures. The posterior segments of the lower lung lobes with the peripheral and sub pleural distribution can be seen on the axial images as bilateral scattered ground-glass opacity and air-space consolidation. Any automated solution developed to diagnose COVID-19 should also take into account other respiratory problems since CXR and CT are advised for a variety of pulmonary abnormalities in order to produce a more complete and reliable diagnostic system.

## **2 Computer Aided Diagnosis**

By providing a "second opinion" based on known similar cases using rule-based inference techniques, Artificial Intelligence (AI) approaches, or Content Based Image Retrieval (CBIR), CAD systems assist doctors in making diagnoses. It has been demonstrated that using CAD in



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conjunction with a doctor's diagnosis increases the radiologists' diagnostic precision, lessens the strain of a rising workload, decreases the number of cancer cases missed because of weariness, overlooking, or data overload, and increases inter- and intra-reader variability.

### **3 Role of Image Processing and Machine Learning In Cad**

In CAD of lung disorders based on analysis of chest CT various image processing techniques are essential for dataset preparation. The chest 6 CTs must first be made suitable for further processing by removing the noise and improving the quality of the image. This is achieved by using image enhancement techniques. Regions of Interest (ROIs) must be extracted after the image has been improved, which requires the application of image segmentation techniques. The ROIs should then be described quantitatively and this involves use of feature extraction techniques. One of the most popular methodologies in CAD for medical imaging is now machine learning. This method falls under the category of supervised learning and uses classifiers that have been constructed and trained to assign labels to new cases based on a collection of features derived from previously labelled data. The features may include the raw image data, higher level descriptive features derived from the images, or additional clinical data. However, using too many features in the classification algorithm can lead to problems, particularly if there are irrelevant features. Due to the small size of the training data, this can result in overfitting, where noise or irrelevant features may affect the classification judgement. This requires the use of feature selection or dimensionality reduction techniques.

### **4 Computed Tomography**

This new technique of computed tomography (CT) reconstructs a cross- sectional image of the body from a 'virtual pile of X-ray photographs'. A tomographic image is an image of a slice through the body. The word 'tomography' comes from the Greek: tomos means slice, graphein stands for 'to write'. So, tomography literally means 'writing slices'. Structures and lesions that were previously impossible to discern with clarity are now observable. The principle behind CT is a thin collimated beam of X-rays passes through the body to a detector that measures the transmitted intensity. The collimator is a set of narrow lead tubes or an array of small holes in a lead plate, resulting in a thin straight beam of X-rays. As the source and detector are transported past the body together, measurements are taken at numerous locations. The device is then slightly rotated about the body axis and scanned once more. This is repeated at, for example, 1° intervals for 180°. The intensity of the transmitted beam for the many points of each scan, and for each angle, are sent to a computer that reconstructs the image of the slice. The image is presented on a computer monitor. Note that the imaged slice is perpendicular to the long axis of the body. For this reason, CT is sometimes called computed axial tomography (CAT), although



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the abbreviation CAT, as in CAT scan, can also be read as computer-assisted tomography. But how is the image formed? We can think of the slice to be imaged as being divided into many tiny picture elements or pixels, which could be squares as in CT, the width of each pixel is chosen according to the width of the detectors and/or the width of the X-ray beams. This determines the resolution of the image, which is typically about 2 mm. An X-ray detector measures the intensity of the transmitted beam after it has passed through the body. Subtracting this value from the intensity of the beam at the source the total absorption. Note that only the total absorption along each beam line can be measured: the absorption by all the pixels in a line. To form an image, The CT scanner Computed tomography is an imaging technique that produces cross-sectional images, representing in each pixel the local X-ray attenuation properties of the body. The first experimental set-up of Hounsfield in 1970 worked with the so-called translation/rotation principle. A thin beam of X-rays was generated through the use of a collimator and a single detector element was used to measure the attenuated intensity. Different positions were measured by translating this set-up. After an entire set of parallel measurements had been acquired, the Principle was used in what is now called the 1st generation of CT scanners the only significant difference between the second generation CT scanners and the original design was the ability to acquire a limited number of measurement values concurrently. In Hounsfield's first commercially available scanner a total of 180 projections were obtained in steps of  $1^\circ$  with 160 measurement values each. The acquisition of those 28.800 measurement values took five minutes. From that data an image of  $80 \times 80$  pixels was reconstructed. With such a scanner, a head examination requiring six slices took about half an hour. Therefore, physicists were aiming at shortening the examination times. This was made possible with the advent of 3rd generation CT scanners, which obtain a full 'fan-beam' projection by covering the entire measuring field with a 1D array of detector elements arranged on an arc. This not only avoided the slow translation movements, but also improved the efficiency of using the output of the X-ray tube. A donut-shaped gantry with a large hole makes up a third generation CT scanner. . Head, body, arms or legs have to be in the middle of the scanner to make a cross-sectional image. The patient is moved in and out on a motor-controlled table. The slice thickness is usually 0.5 to several mm and the spatial resolution (in the cross section) is roughly 1 mm at  $512 \times 512$  pixels per slice. Within the ring of the CT scanner an X-ray tube is placed opposite a detector array with up to 1200 detecting elements, which receive the photons that went through the patient. If one measurement has been done this way, the source and detector rotate over a small angle (roughly  $1^\circ$ ) and a new measurement is taken. The scanner repeats this procedure until a rotation of  $180^\circ$  has been reached. Then all thousands of measurements for reconstructing one slice have been done.



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## **5 Advent of Machine Learning**

Image processing techniques have tremendously helped the modern machine vision systems. However, the recent advancements have paved way to new way of solving problems through machine learning. Machine vision aims to solve a problem by making a machine learn the tactics to solve the problem which humanity takes a generation to solve or what is inbuilt with everyone naturally. The former Rule-based systems made up of tools or techniques driven by perceived features; these hand designed programs can sort out the challenges and arrive at conclusions. However, the same program does not answer or does not provide an optimal solution for edge cases. Hence the situation of adaptive learning can be made possible only when a machine can learn from its' experience. Hence 'Machine Learning' is the act of machine learning a problem and various aspects of hidden knowledge of the problem domain like a human being so that it can act on the data enforced by the domain and dynamically solve the challenges and decides an output. This capability of Machine Learning is possible by generalizing the problem domain as linear regression problem and logistic regression problem. This effort of research uses cervical cancer and applies machine learning on the data to obtain the decision of whether a given image has a cancer cell.

### **5.1 Supervised Vs Unsupervised Vs Semi-Supervised**

Supervised model in Machine learning is when model decides based on predetermined facts. The features and the outcome of each feature are available to the model for learning the features and the objective. Because such models know the outcome of the 'feature-set', it is very much comfortable to predict any such facts. Unsupervised models where the result is known, only the input data is available. Based on what is in the data machine learning model should be able to produce insights on the data. Semi-supervised models are the combination of supervised and unsupervised scenarios.

### **5.2 Emergence of Deep Learning**

The dependency of supervised learning is a limitation where the problem is very dynamic. 'Machine Vision' systems demand solutions in conditions where there are no test facts available or they were only partially available. When no benchmark facts are available, the conditions require machine learning to learn and understand nuances of data from their representation in an adaptive manner. Any of the real world activities or incidents can be represented in the form of activities and can be represented in an automation system. Usually the data in the form of features and objectives. It is easy hypothetically made a decision or search and analyse better when data points are well structured. Hence, the representation of data has a significant impact on



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the performance of machine learning algorithms. Figure 1.1 presents the distribution of features which are readily separable as Cartesian coordinates and the scattered is polar coordinates. The problems associated with machine learning can be best solved when represented structurally.

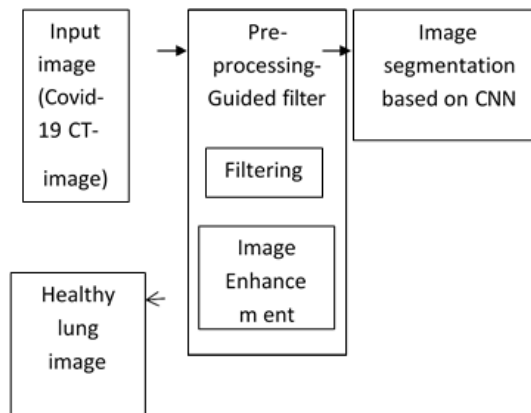
## **6 Overview of the Proposed System**

Actually, the unanticipated Catastrophe—which no one could have predicted—has been the new Coronavirus. Since a huge number of people need to be tested, it has become a pandemic and prompted concerns about the health infrastructure and services available. The prevalent diagnostic procedure is RT-PCR. However, there are a number of problems with RT-PCR testing, including the fact that it relies solely on one strategy even though it is becoming more challenging for most nations to obtain the necessary number of testing kits and there have been some instances of false positive results. All of these considerations make it necessary to look into various testing procedures; it is not sufficient to rely solely on one way. Apart from RT-PCR testing, Chest CT can be a great tool to know about the status and severity of COVID-19. Person a call has to be made on the COVID-19 status and that needs very high accuracy and expertise and again there will be a shortage of the expertise. Therefore, a COVID-19 detection system has been developed as a potential answer to this issue. This method can help the medical specialists in their analysis of the report before they reach a decision. As observed, Deep Learning techniques, especially Fully Convolutional Neural Network (FCNN) have proven to be outstanding in medical image classification and analysis, and as our task is similar to medical image classification, FCNN is a good choice for our use case. So, we analyzed four different FCNN architectures on CT for Covid-19 Diagnosis. Pre-training of the models is done on ImageNet datasets. Results have been produced by using transfer learning. A comparative study of the results obtained with different architecture reveals that structures based on FCNN have great potential for Covid-19 diagnosis and detection.



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## 6.1 System Architecture



**Figure 1:** Segmentation based on CNN

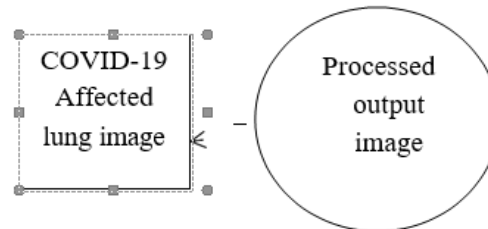
## 6.2 Image Acquisition

All of the patients who had signed up for the study had their CT scans done on a gem CT scanner (GE Discovery CT750HD; GE Healthcare, Milwaukee, WI), and they were all positioned in supine with their bilateral arms elevated and put next to their bilateral ears. Without the use of contrast agents, all of the patients underwent end- inspiration CT scans. Related parameters for chest CT scanning were listed as follows:

- Field of view (FOV), 36 cm;
- Tube voltage, 100 kV;
- Tube current, 350 mA;
- Noise index, 13;
- Helical mode;
- Section thickness, 5 mm;
- Slice interval, 5 mm;
- Pitch, 1.375;
- Collimation 64×0.625 mm;
- Gantry rotation speed, 0.7 s;
- Matrix, 512 × 512;



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**Figure 2:** *Proposed system architecture*

### 6.3 System Methodology

#### 6.3.1 Pre-processing

The reconstruction slice thickness 1 mm with an interval of 0.8 mm; Scan range from apex to lung base; the mediastina window: window width of 200 HU with a window level of 35 HU, and the lung window: window width of 1500 HU with a window level. The preprocessing phase's goal is to apply potential image enhancing techniques to the photos in order to achieve the desired visual quality. Image Acquisition Pre-processing. In the proposed method guided filter is used for preprocessing.

Guided filter is generic concept for edge preserving smoothing and structure transferring filtering.

Step 1: Read the input image.

Step 2: Enter the values of  $r$  and  $\epsilon$  where  $r$  is the local window radius and  $\epsilon$  is the blur degree of the filter.

Step 3: Calculate the values: Mean of  $I$ , Variance of  $I$ , Mean of  $P$ , Average cross product of  $I$  and  $P$ .

Step 4: Compute the value of linear coefficients.  $A = (\text{cross\_IP} - \text{mean\_I} * \text{mean\_P}) / (\text{var\_I} + \epsilon)$   $b = \text{mean\_P} - a * \text{mean\_I}$

Step 5: Compute the mean of  $a$  and  $b$

Step 6: Obtain the filtered output image  $Q$  using mean of  $a$  and  $b$   $Q = \text{mean\_a} * I + \text{mean\_b}$

#### 6.3.2 Segmentation based on FCNN

Semantic segmentation tasks are commonly solved using the Fully Convolutional Neural Networks (FCNN)-based segmentation technique in computer vision. FCNNs are a specific sort of neural network design that effectively processes images of any size and generates segmentation maps at the pixel level.

Architecture: Encoder-decoder architecture commonly makes up FCNNs. A number of



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convolutional layers make up the encoder portion, which gradually down samples the input image to capture high-level characteristics. The up sampling layers in the decoder component regain the spatial resolution and create a dense segmentation map.

**Training data:** A dataset comprising input images and associated pixel-by-pixel ground truth labels is required to train an FCNN for segmentation. Each pixel in the ground truth label stands for a segmentation class or category (such as an object, background, etc.).

**Training process:** A loss function like cross-entropy or Dice loss is used to compare the output segmentation map to the ground truth labels after feeding the FCNN with input pictures during training. Back propagation and gradient descent optimisation Algorithms are used to update the network's weights in an effort to reduce loss.

**Inference process:** Once the FCNN has been trained, new, unexplored images can be segmented using it. The output segmentation map is obtained once the input image has been routed through the network. In the segmentation map, each pixel represents a predicted class or category.

**Post-processing:** The results of the segmentation may be improved using post-processing techniques, depending on the particular task and application. For smoother bounds, this may entail applying morphological processes, filtering out tiny or noisy regions, or employing conditional random fields. Instance segmentation, semantic segmentation, object segmentation, and other segmentation tasks have all been successfully completed using FCNNs. U-Net, SegNet, and Deep Lab are notable FCNN architectures, each with its own upgrades and tweaks.

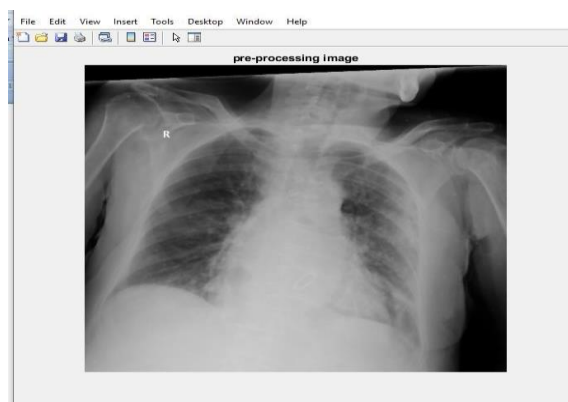
## 7 Result and Output



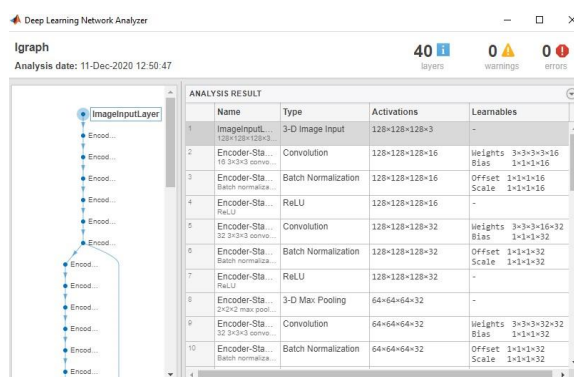
**Figure 3:** *Input image*



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**Figure 4:** *Pre-Processing Image*



**Figure 5:** *Trained data using DeCoVNet*



**Figure 6:** *Segmented image*



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## 8 Conclusion and Future Work

As COVID-19 has affected lives of the people of whole world, it is important for us to increase the testing as it is the only way to tackle COVID-19. As Real Time - PCR is the only gold standard test, but dependency on only one test alone is insufficient. In our study, we have considered 4 different FCNN based architecture which are originally trained on ImageNet dataset and used the transfer learning technique for transferring the weights. From the results presented above it clear that Mobile Net is the best possible option and also all the 4 models didn't suffer from any kind of overfitting and under fitting. Also, our dataset is neutral with equal images in training and testing of all the three classes. So, FCNN based architectures provide a potential method for alternative testing methodology and help in tackling COVID-19 in the long run. In future as the flow of input data increases, we can further fine tune these models to get even better results, also different FCNN architectures can be developed for detection of other diseases of similar domain. In future work, the system implemented is fully prepared for testing with a considerably larger directory. Automatic discovery of the majority exclusionary features among the classes is a further advantage of FCNN.

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